The effect of different non-linear demand response models considering incentive and penalty on transmission expansion planning

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Abstract— The Transmission Expansion Planning (TEP) problem involves adding new lines to the existing electrical transmission network in order to meet the electrical demand requirements. Demand Response (DR) plays an important role in solving the TEP problem due to the delay in the investment costs. Researchers usually focus on the linear model of DR, while the focus on nonlinear models including power, exponential and logarithmic of DR is small. In this paper and in order to understand which model gives the realistic results, the linear model of DR is studied simultaneously with nonlinear models including power, exponential and logarithmic of DR. Moreover, the effect of incentive and penalty which has been neglected in the studies, is investigated. The study is investigated based on the viewpoint of different participants of the market including Independent System Operator (ISO), Customers and Utilities. In order to prioritize and select the most effective DR program, five characteristics including Peak Reduction, Energy Consumption, Load Factor, Peak to Valley and Customer's Total Cost are extracted from the load curve. Then, using the weighting coefficients obtained by Entropy technique and implementing the TOPSIS and AHP technique, different DR programs are prioritized.

Index Terms— AHP, Customers, Demand Response, Entropy technique, Independent System Operator, Transmission Expansion Planning, TOPSIS, Utilities

I. INTRODUCTION

The Transmission Expansion Planning (TEP) problem involves adding new lines to the existing electrical transmission network in order to meet the electrical demand requirements, taking into account technical and financial constraints during the predefined planning horizon [1].

TEP is a large-scale mixed-integer nonlinear optimization problem which includes many equality and inequality constraints. The techniques used to solve these types of problems can be categorized into three different techniques including evolutionary techniques [2-9], mathematical techniques [10-12] and meta-heuristic techniques [13-17].

The first example for evolutionary technique in solving TEP problems was presented in [4] where TEP was formulated as a load distribution problem and the objective

function and the constraints was modelled by linear functions. The effect of ohmic power losses was ignored and linear load flow was calculated by considering the newly added lines until no overload was found in the system. The other example is [5] where TEP problem was divided into two stages which in the first stage, investment was solved by an evolutionary technique, and in the second stage, generation was solved by a known optimization technique. Sensitivity analysis was used in another studies of evolutionary technique [6-8] to solve TEP problem. In these studies, it is used sensitivity index to determine the added lines. Different algorithms such as load feeding [6], lowest criteria [7] and the optimal load flow [8] was used to make sensitivity index.

Linear programming is the most well-known mathematical technique for solving TEP problem [10]. The TEP problem was divided into two stages including investment and generation where linear planning model and Monte Carlo was used to solve the stages based on DC load flow. The nonlinear planning is another mathematical technique for solving TEP problem where the objective function and some constraints was formulated by nonlinear equations. In this technique, the output result may get stuck in the local solution and this is the main disadvantage of this technique. Mathematical decomposition was used in [12] where was another example for mathematical technique for solving TEP problem.

Meta-heuristic techniques were proposed to use the advantage of the evolutionary and mathematical techniques. An Imperialistic Competitive Algorithm (ICA) is a meta-heuristic algorithm that shows excellent results in different applications. In [13], ICA is used and its superior compared to several other heuristic methods is verified. A parallel SA algorithm which significantly reduced the computation burden and improved quality of the SA solution was proposed in [14]. A greedy randomization adaptive search procedure was investigated in [15]. Particle swarm optimization (PSO) is another heuristic method that has gained lots of attention due to its effectiveness. In [16], this method is used to provide better accuracy by tuning the parameters of a machine learning model. In [18] a novel multiobjective approach to the Stochastic Fractal Search algorithm namely Non-Dominated Ranking SFS (NR-SFS) is introduced and applied to find the optimum solution to the nonlinear constrained problem. The outcome of reference [18] shows the effectiveness of the proposed method in providing secure operation of a microgrid in presence of uncertainties.

Because of the delay in the investment costs, Demand Response (DR) plays an important role in solving the TEP problem [19-21]. DR is essentially a change in the energy

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usage pattern of the end-use customers from its intended power in response to the power changes or incentives [23]. Customers will benefit due to incentives and Independent System Operator (ISO) will benefit due to load reduction in its electrical network. The usefulness of DR has been proved in the United States [24], and other countries [25]. In investment and DR, Data Envelopment Analysis (DEA) plays an important role as well. DEA is a nonparametric method in operations research economics for the estimation of production frontiers. DEA can be addressed through diverse computational, and combinatorial models [26, 27].

In the studies, linear model of DR is usually used, while the focus on nonlinear models including power, exponential and logarithmic of DR is small. It is illustrated that the nonlinear model with power structure of DR gives better results [28]. Also, in [29] the nonlinear model with logarithmic structure of DR is used. In order to understand which model gives the realistic results, the linear model of DR should be studied simultaneously with nonlinear models including power, exponential and logarithmic of DR. In the definition of DR, incentive and penalty is used as one of the main reasons for changing the energy usage pattern of the end-use customers from its intended power which has been neglected in the studies. There are different participants in the market which their viewpoint should be considered. Independent System Operator (ISO), Customers and Utilities are members of the market where has different opinions. In order to prioritize and select the most effective DR program, five characteristics including Peak Reduction, Energy Consumption, Load Factor, Peak to Valley and Customer's Total Cost are extracted from the load curve. Then, using the weighting coefficients obtained by Entropy technique and implementing the TOPSIS and AHP technique, different DR programs are prioritized. On this basis, our contribution in this paper is as follow:

- Find the effect of linear and nonlinear models of DR.
- Find the effect of incentive and penalty.
- Considering the viewpoint of different participants of the market in prioritize DR programs.

On this basis and in the following, the formulation of linear and nonlinear models of DR considering incentive and penalty are presented in 2. In section 3 and 4, incentive and penalty formulation and procedure of DR program prioritization are provided, respectively. Simulation and results are provided in section 5 and finally in section 6, the conclusion are provided.

II. DIFFERENT MODELS OF DR

Elasticity can be defined as the sensitivity of demand to price [28]:

$$E(i, j) = \frac{\partial d(i)}{\partial p(j)} \cdot \frac{p_0(j)}{d_0(i)} \quad j = 1, 2, \dots, 24 \quad (1)$$

where $d(i)$ is the customer demand in i -th hour, $d_0(i)$ is the initial customer demand in i -th hour, $p(i)$ is the spot electricity price in i -th hour, $p_0(i)$ is the initial electricity price in i -th hour. If $B(i)$ is assumed as the benefit of customer during i -th hour, then, the customer benefit (S) can be obtained as follow:

$$S = B(i) - d(i) \cdot p(i) \quad (2)$$

The difference in customer demand with respect to his/her initial demand during i -th hour can be stated as:

$$\Delta d(i) = d(i) - d_0(i) \quad (3)$$

If the customer are paid $A(i)$ for each kWh load reduction during i -th hour, the total incentive during i -th hour can be written as:

$$P(\Delta d(i)) = A(i)(d_0(i) - d(i)) \quad (4)$$

The penalty will be applied for a customer who does not comply with his/her own contract requirements. If the contract level and penalty are stated by $IC(i)$ and $Pen(i)$ during i -th hour, the total penalty during i -th hour can be shown as:

$$PEN(\Delta d(i)) = Pen(i)[IC(i) - \{d_0(i) - d(i)\}] \quad (5)$$

By considering the incentive and penalty, the equation (2) can be rewritten as follow:

$$S = B(d(i)) - d(i) \cdot p(i) + P(\Delta d(i)) - PEN(\Delta d(i)) \quad (6)$$

Based on the classical optimization rules, and to obtain the maximum customer profit, the differentiation of S shall be equal zero.

$$\frac{\partial S}{\partial d(i)} = \frac{\partial B(d(i))}{\partial d(i)} - p(i) + \frac{\partial P}{\partial d(i)} - \frac{\partial PEN}{\partial d(i)} = 0 \quad (7)$$

$$\frac{\partial B(d(i))}{\partial d(i)} = p(i) + A(i) + Pen(i) \quad (8)$$

Linear and nonlinear models including power, exponential and logarithmic are prevalent for the customer's response. In the following, Taylor expansion of $B(i)$ has been shown for these different structures:

$$\left\{ \begin{array}{ll} B(i) \cong B_0(i) + \rho_0(i)(d(i) - d_0(i)) \cdot \left\{1 + \frac{d(i) - d_0(i)}{2E(i, i)d_0(i)}\right\} & \text{linear} \\ B(i) \cong B_0(i) + \frac{\rho_0(i)d(i)}{1 + E(i, i)^{-1}} \left\{\left(\frac{d(i)}{d_0(i)}\right)^{E(i, i)^{-1}} - 1\right\} & \text{power} \\ B(i) \cong B_0(i) + \rho_0(i)d(i) \cdot \left\{1 + \frac{1}{E(i, i)} \left[\ln\left(\frac{d(i)}{d_0(i)}\right) - 1\right]\right\} & \text{exponential} \\ B(i) \cong B_0(i) + \rho_0(i)d_0(i)E(i, i) \cdot \left\{EXP\left(\frac{d(i) - d_0(i)}{E(i, i)d_0(i)}\right) - 1\right\} & \text{logarithmic} \end{array} \right. \quad (9)$$

The differentiation of $B(i)$ can be obtained as follow:

$$\left\{ \begin{array}{ll} \frac{\partial B(i)}{\partial d(i)} = \rho_0(i) \cdot \left\{1 + \frac{d(i) - d_0(i)}{E(i, i)d_0(i)}\right\} & \text{linear} \\ \frac{\partial B(i)}{\partial d(i)} = \frac{\rho_0(i)}{1 + E(i, i)^{-1}} \left\{\left(\frac{d(i)}{d_0(i)}\right)^{E(i, i)^{-1}} - 1\right\} + \frac{\rho_0(i)d(i)}{1 + E(i, i)^{-1}} \left\{\frac{E(i, i)^{-1}}{d_0(i)} \cdot \left(\frac{d(i)}{d_0(i)}\right)^{E(i, i)^{-1}-1}\right\} & \text{power} \\ \frac{\partial B(i)}{\partial d(i)} = \rho_0(i) + \frac{\rho_0(i)}{E(i, i)} \ln\left(\frac{d(i)}{d_0(i)}\right) & \text{exponential} \\ \frac{\partial B(i)}{\partial d(i)} = \rho_0(i) \cdot EXP\left(\frac{d(i) - d_0(i)}{E(i, i)d_0(i)}\right) & \text{logarithmic} \end{array} \right. \quad (10)$$

By Substituting (8) and (10), the following equation is obtained:

$$\left\{ \begin{array}{ll} \rho(i) + A(i) + Pen(i) = \rho_0(i) \cdot \left\{1 + \frac{d(i) - d_0(i)}{E(i, i)d_0(i)}\right\} & \text{linear} \\ \rho(i) + A(i) + Pen(i) = \frac{\rho_0(i)}{1 + E(i, i)^{-1}} \left\{\left(\frac{d(i)}{d_0(i)}\right)^{E(i, i)^{-1}} - 1\right\} + \frac{\rho_0(i)d(i)}{1 + E(i, i)^{-1}} \left\{\frac{E(i, i)^{-1}}{d_0(i)} \cdot \left(\frac{d(i)}{d_0(i)}\right)^{E(i, i)^{-1}-1}\right\} & \text{power} \\ \rho(i) + A(i) + Pen(i) = \rho_0(i) + \frac{\rho_0(i)}{E(i, i)} \ln\left(\frac{d(i)}{d_0(i)}\right) & \text{exponential} \\ \rho(i) + A(i) + Pen(i) = \rho_0(i) \cdot EXP\left(\frac{d(i) - d_0(i)}{E(i, i)d_0(i)}\right) & \text{logarithmic} \end{array} \right. \quad (11)$$

The solution of the above equations is obtained as follows:

$$\left\{ \begin{array}{ll} d(i) = d_0(i) \{1 + E(i, i) \cdot \frac{\rho(i) - \rho_0(i) + A(i) + Pen(i)}{\rho_0(i)}\} & \text{linear} \\ d(i) = d_0(i) \cdot \left(\frac{(A(i) + Pen(i) + \rho(i) + \rho_0(i)) \cdot E(i, i) + A(i) + Pen(i) + \rho(i)}{\rho_0(i) \cdot (E(i, i) + 1)} \right)^{E(i, i)} & \text{power} \\ d(i) = d_0(i) \cdot \exp\left(\frac{E(i, i) \cdot (A(i) + Pen(i) + \rho(i) - \rho_0(i))}{\rho_0(i)} \right) & \text{exponential} \\ d(i) = d_0(i) \{1 + E(i, i) \cdot \ln\left(\frac{\rho(i) + A(i) + Pen(i)}{\rho_0(i)} \right)\} & \text{logarithmic} \end{array} \right. \quad (12)$$

The above equations represent single period model, while in the following, multi period model are presented:

$$\left\{ \begin{array}{ll} d(i) = d_0(i) \{1 + \sum_{j=1}^{24} E(i, j) \cdot \frac{\rho(j) - \rho_0(j) + A(j) + Pen(j)}{\rho_0(j)}\} & \text{linear} \\ d(i) = d_0(i) \cdot \prod_{j=1}^{24} \left(\frac{(A(j) + Pen(j) + \rho(j) + \rho_0(j)) \cdot E(i, j) + A(j) + Pen(j) + \rho(j)}{\rho_0(j) \cdot (E(i, j) + 1)} \right)^{E(i, j)} & \text{power} \\ d(i) = d_0(i) \cdot \exp\left(\sum_{j=1}^{24} \frac{E(i, j) \cdot (A(j) + Pen(j) + \rho(j) - \rho_0(j))}{\rho_0(j)} \right) & \text{exponential} \\ d(i) = d_0(i) \{1 + \sum_{j=1}^{24} E(i, j) \cdot \ln\left(\frac{\rho(j) + A(j) + Pen(j)}{\rho_0(j)} \right)\} & \text{logarithmic} \end{array} \right. \quad (13)$$

III. INCEPTIVE AND PENALTY FORMULATION

For linear incentive and penalty, the values are considered 100 and 50 \$/kW.h, respectively. For nonlinear incentive and penalty, it is used the following equations:

$$A(t) = \frac{d_0(t)}{d_{\min(\text{peak interval})}} A \quad (14)$$

$$P(t) = \frac{d_0(t)}{d_{\min(\text{peak interval})}} Pen \quad (15)$$

where A is linear incentive equal to 100 \$/kW.h, Pen is linear penalty equal to 50 \$/kW.h, $d_0(t)$ is demand at time t, $d_{\min(\text{peak interval})}$ is the minimum demand in the peak period, A(t) is nonlinear incentive and P(t) is nonlinear penalty.

IV. PROCEDURE OF DR PROGRAM PRIORITIZATION

The main goal of this section is to prioritize and select the most effective DR program where the load characteristics approaches the desired one. For this purpose, five characteristics including Peak Reduction, Energy Consumption, Load Factor, Peak to Valley and Customer's Total Cost are extracted from the load curve. Then, using the Entropy technique [30], weighting coefficients are given to the above characteristics. Since each market participant have its own viewpoint, there are different weighing coefficients for each one. The weighting coefficients for different market participants (ISO, Utility and Customer) versus load features are provided in Table I. Based on the weighting coefficients and implementing the TOPSIS [31], the prioritization of the different DR programs is obtained.

TABLE I: THE WEIGHTING COEFFICIENTS FOR DIFFERENT MARKET PARTICIPANTS (ISO, UTILITY AND CUSTOMER) VERSUS LOAD FEATURES

Feature	Peak Reduction	Energy Consumption	Load Factor	Peak to Valley	Customer's Total Cost
ISO	0.3	0.1	0.3	0.2	0.1
Utility	0.1	0.1	0.2	0.1	0.5
Customer	0.1	0.2	0.1	0.1	0.5

In the following, the market regulator should determine each market participant's weight. Table II shows a pair

comparison of market participants based on expert's viewpoints. The AHP technique [32] is used to obtain decision maker weights where has been shown in the final column of Table III [33]. As can be seen, the opinion of the ISO is in the first rank with 57 % and opinion of the customer and utility is in the second and third rank with 29 % and 14 %. Finally, the priority of DR programs are obtained by market regulator.

TABLE II: PAIR COMPARISONS BY AHP TECHNIQUE [33]

Feature	ISO	Utility	Customer	Weight
ISO	1	4	2	0.57
Utility	0.25	1	0.5	0.14
Customer	0.5	2	1	0.29

V. SIMULATION RESULTS

To find the effect of linear and nonlinear models of DR and the effect of incentive and penalty, the DR is applied on a typical load considering the following scenarios:

1. Linear Demand Response (LDR);
2. Nonlinear Demand Response (NLDR) based on Power modelling;
3. NLDR based on Exponential modelling;
4. NLDR based on Logarithmic modelling;
5. DR considering linear incentive and penalty;
6. NLDR based on Power modelling considering linear incentive and penalty;
7. NLDR based on Exponential modelling considering linear incentive and penalty;
8. NLDR based on Logarithmic modelling considering linear incentive and penalty;
9. LDR considering nonlinear incentive and penalty;
10. NLDR based on Power modelling considering nonlinear incentive and penalty;
11. NLDR based on Exponential modelling considering nonlinear incentive and penalty;
12. NLDR based on Logarithmic modelling considering nonlinear incentive and penalty;

In Table III, self- and cross-elasticity of load have been provided.

TABLE III: SELF- AND CROSS-ELASTICITY OF LOAD

	Valley	Off-Peak	Peak
Valley	-0.10	0.01	0.012
Off-Peak	0.01	-0.10	0.016
Peak	0.012	0.016	-0.10

In Fig. 1, the effect of different load modelling on DR (scenarios 1-4) has been shown. As can be seen, the load has been significantly decreased in peak period for all linear, power, logarithmic and exponential model types. This decrease is more in linear model among other models. In off-peak period, the load has slightly increased and in valley period, the load has increased as it is desired for researchers.

In Fig. 2 the effect of different load modelling on DR considering linear incentive and penalty (scenarios 5-8) has been shown. Similar to the previous, load has significantly

decreased in all four models in the peak period and the largest decrease is related to the linear model. In off-peak period, the load has slightly increased. In valley period, the results of the linear, logarithmic and exponential models are almost similar to each other, but the results of the power model have a large difference with the rest of the methods. By comparing Fig. 1 and Fig. 2, the effect of incentive and penalty can be found. The most significant issue is that in the linear model with the presence of incentive and penalty, the amount of reduction is much higher than the linear model without incentive and penalty, which shows that the use of appropriate DR model is essential.

In Fig. 3 the effect of different load modelling on DR considering nonlinear incentive and penalty (scenarios 9-12) has been shown. Similar to the results obtained in Fig. 2, the above results are obtained.

Fig. 1. The effect of different load modelling on DR (scenarios 1-4)

Fig. 2: The effect of different load modelling on DR considering linear incentive and penalty (scenarios 5-8)

Based on the section 4, prioritization of scenarios are obtained which can be seen in Table IV. Based on the above results, the NLDR based on Logarithmic modelling considering linear incentive and penalty leads to the best solution. In fact, this method is a realistic solution which is far from bad solutions is close to best solutions. Based on the above results, the NLDR based on Logarithmic modelling considering linear incentive and penalty leads to the best solution. In fact, this method is a realistic solution which is far from bad solutions is close to best solutions.

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Fig. 3: The effect of different load modelling on DR considering nonlinear incentive and penalty (scenarios 9-12)

TABLE IV: PRIORITIZATION OF SCENARIOS BASED ON SECTION 4

Priori ty	Scenar io	Peak Reducti on	Energy Consumpt ion	Load Factor	Peak to Valley	Custome r's Total Cost
1	8	7.7723	690496	91.59 46	6817. 16	1359587 85
2	12	7.7549	690352	91.55 82	6819. 79	1358785 37
3	1	7.3973	686272	90.66 56	7257. 79	1348491 01
4	5	6.5724	679440	88.97 04	7382. 74	1310401 80
5	9	6.5117	678937	88.84 69	7391. 93	1307599 42
6	7	6.3882	698233	91.25 15	6977. 51	1371107 47
7	11	6.3143	698478	91.21 14	6982. 23	1370941 74
8	4	6.1631	692817	90.32 64	7418. 18	1372526 14
9	3	6.1248	696015	90.70 63	7335. 39	1377152 77
10	6	5.4293	713493	92.30 02	6029. 53	1397596 86
11	10	5.4293	713493	92.30 02	6029. 53	1397596 86
12	2	4.6007	700665	89.85 35	7397. 25	1388472 95

Figure 4 shows the priority of scenarios based on legislator's viewpoint which is considered main participant' viewpoint in the market. As can be seen, the NLDR based on Logarithmic modelling considering linear incentive and penalty is in the top rank and NLDR based on Logarithmic modelling considering nonlinear incentive and penalty is in the next step. On this basis, the legislator will assure that not also reliability issues have been considered but also participant's benefit are provided by running the NLDR based on Logarithmic modelling considering linear incentive and penalty.

In order to further investigate the proposed technique, the above technique is implemented on the IEEE 57-bus electrical network. To do this, DR are performed while the load of buses 9, 12, 16 and 18 are considered as office,

commercial, residual and residual, respectively. Similar to previous, three scenarios are performed including:

- Without considering incentive and penalty;
- Considering linear incentive and penalty;

- Considering nonlinear incentive and penalty;

Fig. 4: The prioritization of different scenarios based on legislator's viewpoint

Figures 5 up to 7 show the office-building load of bus 9 in three different scenarios including after DR, after DR considering linear incentive and penalty and after DR considering nonlinear incentive and penalty. As can be seen from fig. 5, the results are similar in peak and off-peak periods, but the results of DR for power modeling is different in valley period. These results can be true for Fig. 6 and Fig. 7. The comparison between Fig. 5 and other figures, means Fig. 6 and Fig. 7, reveals the effect of incentive and penalty on DR. As can be clear, the reduction in linear model is considerable which means use of appropriate DR model is essential.

Fig. 5: Office-building Load of bus 9 in base and after DR

Figures 8 up to 10 show the commercial load of bus 12 in three different scenarios including after DR, after DR considering linear incentive and penalty and after DR considering nonlinear incentive and penalty. In this load; means commercial load; the results are match again with previous load; office-building load. With the presence of linear/nonlinear incentive and penalty, the linear model makes more reduction.

Figures 11 up to 13 show the residual load of bus 16 in three different scenarios including after DR, after DR considering linear incentive and penalty and after DR considering nonlinear incentive and penalty. The results show that the use of appropriate DR model is essential.

Based on the section 4, prioritization of scenarios are obtained as follow:

Fig. 6: Office-building Load of bus 9 in base and after DR considering linear incentive and penalty

Fig. 7: Office-building Load of bus 9 in base and after DR considering nonlinear incentive and penalty

Fig. 8: Commercial Load of bus 12 in base and after DR

- Bus 9: DR considering linear incentive and penalty;
- Bus 12: DR considering linear incentive and penalty;
- Bus 16: DR considering nonlinear incentive and penalty;
- Bus 18: DR considering nonlinear incentive and penalty;

Fig. 9: Commercial Load of bus 12 in base and after DR considering linear incentive and penalty

Fig. 10: Commercial Load of bus 12 in base and after DR considering nonlinear incentive and penalty

Fig. 11: Residual Load of bus 16 in base and after DR

Fig. 12: Residual Load of bus 16 in base and after DR considering linear incentive and penalty

Fig. 13: Residual Load of bus 16 in base and after DR considering nonlinear incentive and penalty

It is worth to mention that for sample load, the NLDR based on Logarithmic modelling considering linear incentive and penalty leads to the best solution while for above loads, DR considering linear/nonlinear incentive and penalty leads to the best solution. This means that choosing the best solution depends on the load pattern. In other words, a method must be selected to consider all participant's viewpoint in the market and have a realistic behaviour, and this should be considered in the planning.

As the final aim of this paper is using DR results in TEP problems, in the following the TEP problem is solved by considering the realistic participation of buses 9, 12, 16 and 18 by the hierarchical method. Then the results are compared with logarithmic DR obtained in [29]. To do this and as the TEP problem must be performed in maximum load (worst case), the peak demand time should be specified. For this, the load of buses 9, 12, 16 and 18 are combined and the peak demand time is determined. The peak demand time is found as 20:00 and TEP problem solved. In Table V, output results of TEP problem and its comparison with [29] are provided.

TABLE V: OUTPUT RESULTS OF TEP PROBLEM AND ITS COMPARISON WITH [29]

Item	Loss (MW)	Cost of Loss (\$/h)	Cost of Generation (\$/h)	Cost of Line Construction (\$/h)	Total Cost (\$/h)
The results of [29]	9.8771	34.3722	37854	515.6575	38404
The obtained results	9.7228	33.8353	36462	515.5045	37011

When appropriate DR is applied, the electrical network peak reduces which makes reduction of stresses on electrical equipment. Also, the lines congestion are removed and the subsequently lines capacity are released and fewer lines are needed. This decreases the different costs and ultimately reduces the total cost significantly. As can be seen from the Table V, the loss is decreased 0.1543 MW. The other items, including cost of loss, cost of generation, and cost of line construction are decreased 0.5365, 1383 and 0.153 \$/h which makes reduction of total cost equal to 1393 \$/h.

VI. CONCLUSION

In this paper, the linear model of DR is studied simultaneously with nonlinear models including power,

exponential and logarithmic of DR. Moreover, the effect of linear/nonlinear incentive and penalty is investigated. The results show that the use of appropriate DR model is essential. The study is investigated based on the viewpoint of different participants of the market including Independent System Operator (ISO), Customers and Utilities. The results show that choosing the best solution depends on the load pattern. In other words, a method must be selected to consider all participant's viewpoint in the market and have a realistic behaviour, and this should be considered in the planning.

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