Development of Optimal Day-Ahead Electricity Pricing Scheme using Real Coded Genetic Algorithm under Demand Response Environment

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Abstract. Real-time pricing in a Smart Grid scenario allows consumers to move their time-insensitive loads to off-peak hours and maintains the power balance between the demand side and supply side. This scheme has a strong impact on customer behaviour, network operations, and overall control of the power grids. In this proposed work, Real coded Genetic Algorithm (RGA) is used to develop a Day Ahead Real-Time electricity-Pricing (DARTP) model. The established scheme maximizes the benefit of the energy provider without reducing the minimum daily consumption rate, the consumer response to the reported electricity prices, and the constraints of distribution networks. The RGA results demonstrate that the calculated optimal prices bring higher benefits for consumers and energy providers than the posting of market prices directly to consumers on the day ahead. The proposed setup is tested with a 32-node distribution bus system. Simulation results reveal that the deployed methodology will help the participants to shift the peak load time to base load time by receiving optimal DARTP, thereby reducing excessive consumption made during the instance of peak load. The obtained DARTP will be sent to the consumers through the deployment of an Advanced Metering System.

1. Introduction

In the existing power system infrastructure, the control priority is given to the supply side rather than the demand-side by assuming consumers are not willing to change their consumption behaviour. Moreover, there is no possibility to communicate with the consumer. Hence, the demand during base load hours is mitigated by increasing the generation, which leads to a higher generation cost. A demand present in the off-peak hours is met by a cost-efficient base load plant. The wholesale electricity prices will be fluctuating many times in a day. The employment of Smart Grid changed the entire scenario, where bidirectional communication is possible. The varieties of time-based-price response schemes are possible by the implementation of the Advanced Metering System.

The analysis of the strength and weaknesses of the available tools for forecasting the energy cost is reviewed in [1]. A well-balanced market clear pricing model was formulated as a mixed problem in [2]. However, the energy cost is derived from the number of generators utilized for providing power. The price-based demand response model is infused with DisCo’s short-term decision in [3]. The maximization of DisCo’s expected profit is taken into account but consumer’s demand and sophistication are not considered. A demand response program was designed to reduce the peak to load the average ratio in [4]. Here only a limited number of messages are permitted to interact and find
the optimal price. The real-time prices will be fixed by interacting with Independent System Operators (ISO) and Generation Companies (GenCos) [5]. Interaction with consumers is not preferred. A new approach is proposed to the pricing scheme, where a diversified incentive package is given to the consumer based on time and situation. However, the contributors assume the demand quantities and supply [6]. In [7] hourly-based real-time pricing scheme was proposed and implemented for industrial facilities. The supplier’s profit, consumer sophistications were not taken into account, while considering the production targets.

In [8], the load uncertainty factor was added in the RTP model with three different uncertainties viz... Unknown distribution model, Gaussian uncertainty, and bounded uncertainty models. The optimal price is obtained for these types of load uncertainties. RTP model with power fluctuating factor is included in the objective function and the system was analyzed offline and online [9]. Consensus-based Altering Direction Multiplier Method (ADMM) for solving demand response was proposed in [10]. Three DC-OPF algorithms were analyzed with demand response. The calculation of optimal real-time pricing is not considered as the main criteria. An optimization model was proposed with the time-varying load as a constraint to analyze consumer consumption [11] where power losses and renewable energy are taken into account. The incentive-based response program was modeled using curtailable services and available market prices. To stimulate consumer response model based on demand variation is proposed in reference [12-13] but the tie based pricing model was not taken into account. An optimization model was proposed for adjusting the load in response to hourly electricity prices [14] but the energy provider's profit was not considered for modeling the price uncertainty.

An optimal RTP approach was developed using Demsi, a demand response simulator in [15]. This DemSi simulator was used by the retailer during the energy shortage situation. The consumer response model is integrated with Electricity mark complex adaptive system in [16] and the effect upon RTP on consumer bill, peak demand, and peak price under the smart grid paradigm is investigated. Aiming maximum welfare for the consumers and minimizing the cost of the energy providers, multiple RTP schemes are proposed in [17-18]. These models received much attention and were cited by many authors [19-20]. Still, there is a gap to find optimal RTP using the optimization technique, which is feasible for the consumer and energy provider.

A holistic model of RTP is focused to overcome the RTP barrier. The objective function formulated in this work aims to increase the energy provider's gain without compromising consumer's benefit and improving the demand elasticity. In this proposed model, each consumer is integrated with a bidirectional communication facility of the smart meter, which is not available in the present metering system. Since the consumers are unaware of RTP, the excess amount is incurred due to a change in load pattern affects their social welfare and economy. The aforementioned issues have stimulated the authors to incorporate the necessary information to be made available in real-time with our proposed scheme with the help of smart metering infrastructure.

The proposed framework is based on the concepts of a smart grid, as it is depicted in Figure 1. It indicates that each consumer is facilitated smart meter along with an Energy management system. These smart meters are connected with the utility through Advanced Metering Infrastructure (AMI) that allows bidirectional communication between energy providers and the consumer. In this context, the authority empowers energy distributors with the means to determine electricity prices, rather than setting fixed electricity rates, so that the interests of both end-users and energy suppliers are safeguarded. To optimally calculate the Day-Ahead prices by the energy provider, they will be accessing the Day-Ahead market prices, distribution network data, and consumer demand data. The AMI will be utilized to communicate these DA prices to consumers.
2. Problem Formulation

The proposed model discussed in this research is developed as an optimization problem. The suggested technique is used to estimate the real-time price to optimize the gain of an energy supplier that provides power to consumers linked to the distribution system. To accurately model the consumer behaviour, many factors are discussed here, including the benefit of consumers, the daily minimum energy usage, and the response of consumers to DARTP reflected by an economic demand model. Constrains on distribution networks are also taken into account in this proposed model. The following is the mathematical formulation of the suggested structure.

2.1 Objective Function

The aim is to increase the profitability of the energy supplier. It is derived as the variation between its profit due to selling the energy to the consumer and the amount spent to purchase the energy from the electricity market.

\[
Max \sum_{t=1}^{2N} \left( \sum_{c=1}^{n_c} D_c(t) \cdot p_c(t) - P_{\text{purch}}(t) \cdot P_{\text{mp}}(t) \right)
\]  

Where,

- \(D_c(t)\) - Response of the consumer to energy prices (kWh)
- \(p_c(t)\) - Day Ahead energy cost declared by energy supplier and informed to the individual consumer through Advanced Metering Infrastructure (¢/kWh)
- \(P_{\text{purch}}(t)\) - The volume of power obtained from the marketer by the energy supplier at time \(t\) (kWh)
- \(P_{\text{mp}}(t)\) - Market price of energy at time \(t\) (¢/kWh)
- \(n_c\) - Number of consumers

2.2. Constraints

The following section explains the various constraints associated with the proposed framework to increase the profit of the energy provider and the comfortability of the consumer.

2.2.1 DA Energy Prices and Consumer Response

Every energy consumer has independent control over their consumption as per their needs. Real-time pricing may vary for the individual consumer. The variation of the consumer based on their energy dependency can be modeled. Every individual may adjust the power consumption in response to change in energy prices for obtaining the maximum welfare. The electrical loads can also be
categorized as shift-able (could be put into service at any time throughout the day) and non-shiftable loads (Heating Ventilation and Air Conditioning and illuminating loads).

The work in reference [12] explains the comprehensive simulation mechanism and the effect of RMP, interval based consumers demand. The final sensitive economic demand model in time interval \( t \) is described as follows:

\[
D_c(t) = D_{0c}(t) \left\{ 1 + \frac{\varepsilon_c(t) [P_c(t) - P_{0c}(t)]}{P_{0c}(t)} + \sum_{h \neq t}^{24} \frac{\varepsilon_c(t,h) [P_c(h) - P_{0c}(h)]}{P_{0c}(h)} \right\}
\]

Where,

- \( \varepsilon_c(t) \) - Self elasticity of the demand
- \( \varepsilon_c(t,h) \) - Cross price elasticity of the demand
- \( P_{0c}(t) \) - Seasonal base energy tariff ($/kWh)
- \( D_{0c}(t) \) - Preliminary forecast of the demand (kWh).

The consumers who are active \( P_c(t) \) based on their load level and the base energy prices can be modeled as (2). It is to be noted that the demands at the base level are identified at each hour, and DARTP are the variables to be decided in the process of optimization.

2.2.2 Maximum Limit and Minimum Demand Limit
Consider a practical scenario of consumer response about the rate of consumption which is very stringent, so that the demand limits for each load must be taken into account as shown in the equation (3). \( D^\text{min}_c(t) \)-represents the minimum limit of load, it is applicable for the loads which need to be turned on during the operating horizon. \( D^\text{max}_c(t) \) represents the maximum limit of load, that is, the total amount of power consumed assuming that all the equipment are turned on during the scheduling hours.

\[
D^\text{min}_c(t) \leq D_c(t) \leq D^\text{max}_c(t)
\]

2.2.3 Minimum Daily Consumption
The constraint of energy consumption is given below

\[
\sum_{t=1}^{24} W_{hc}(t) \geq W_{hc}^\text{day}
\]

Where,

- \( W_{hc}(t) \) - Consumer’s energy consumption \( c \) at time \( t \)
- \( W_{hc}^\text{day} \) - Minimum limit of daily energy consumption by consumer \( c \).

2.2.4 Limit on Real-Time Price
To protect consumers from high-energy prices, there must be a daily cap on real-time prices.

\[
P_c(t) \leq P^\text{max}_c(t)
\]

Where,

- \( P^\text{max}_c(t) \) - Price limit for real-time prices.

2.2.5 The revenue limit of the energy supplier from each consumer
Even though the above constraint (5) may save the consumer from high real-time prices quoted by energy providers, it is necessary to include another constraint for avoiding comparatively high RTP frequently. Hence, the revenue of energy providers by selling energy to each consumer must be less or equal to the case that the prices are directly accessed by consumers. According to equation (6), the consumers who actively responded in each hour will be appreciated in terms of incentives.

\[
\sum_{t=1}^{24} D_c(t) P_c(t) \leq K \sum_{t=1}^{24} D_{0c}(t) P_{0c}(t)
\]
Where,
\[ D_{cE}(t) \] - Consumer responses to DA market price.

2.2.6 System Adequacy Constraint
This constraint enables us to ensure the availability of power capacity is sufficient to meet the hourly demand forecast and to retain a reserve margin.

\[ p_{\text{purch.}}^{\text{max}} \geq \text{RESER}(t) + \sum_{c=1}^{n_c} D_c(t) \]  

(7)

Where,
\[ \text{RESER}(t) \] - A reserve held by the supplier of energy
\[ P_{\text{purch}}^{\text{max}} \] - Power capacity of the substation transformer

This proposed framework along with the constraints is solved by the Real-coded Genetic Algorithm to obtain the optimized DARTP.

3. Real coded Genetic Algorithm
The Meta-heuristic optimization algorithms are generally classified as an Evolutionary Algorithm (EA) and Swarm Intelligent (SI) Algorithms. The Genetic Algorithm (GA) is one of the EA based techniques used to find the optimum search space with high accuracy of resolution. GA imitates the genetic process and general evolution principle of biological organisms. In search space, the optimization is achieved with the help of three main genetic operators such as Selection, Crossover, and Mutation. At an earlier stage, the invention of GA is represented with binary values. But, the real-world problems consist of N-dimensional decimal numbers, when it is processed with GA it is represented as a binary number with a fixed length. However, the good properties of the optimization algorithms are limited by binary representations of the variables, particularly at the continuous search space domains. It is overcome by the Real coded Genetic Algorithm (RGA), where the populations are represented by its actual values irrespective of its length. The genetic operators of RGA play a vital role in optimization techniques, where the binary numbers are replaced with floating numbers. Since the selection process does not involve any numbers, it is not necessary to develop a specific scheme for this operation. The existing BGA based selection process is enough for RGA without any restrictions. The crossover and mutation processes have to be adapted with new schemes in a search space to find the optimized real values. The RGA operators are explained in the sub-sections.

3.1 Selection
It is a very essential procedure in a GA to choose the fittest chromosome for the next generation. Based on the higher fitness value, the chromosome will be selected for the concurrent generation. The commonly used selection techniques are Roulette-wheel, tournament selection, and ranking selections. In this work, a tournament selection is used for the process of reproduction. In this selection strategy, "n" individuals are randomly selected from the population and the fittest individual is opted into the next population [21]. This process will continue until the matting pool is filled. Tournaments are often held between pairs of individuals (n=2), although larger tournaments with more number of participants can also be held.

3.2 Crossover Operation
The crossover operator ensures the global search property of the Genetic Algorithm. The substructures of two-parent chromosomes are combined by the cross over to produce new features in the probability range of 0.6-0.9 [22]. The Blend Crossover (BLX-\(\alpha\)) operator and single-point crossover operators are applied to floating-point and integer numbers respectively. The BLX crossover operation for the one-dimensional case is illustrated in Figure 2.
In the sampled search space, the new individuals are picked from the particular variable of fittest parents $p_1$ and $p_2$ uniformly by BLX. The off-spring $y$ is sampled from space $[e_1, e_2]$ as given below.

$$y = \begin{cases} e_1 + \text{rand} \times (e_2 - e_1) & \text{if } p_{\text{min}} \leq y \leq p_{\text{max}} \text{ sampled} \\ \text{otherwise} & \end{cases}$$

Where,

- $e_1 = p_1 - \alpha \times (p_2 - p_1)$
- $e_2 = p_2 + \alpha \times (p_2 - p_1)$

$\text{rand}.$ Uniform random number $\in (0,1)$

In the above equation, $e_1$ and $e_2$ lie between the variable’s upper and lower bounds, $P_{\text{max}}$ and $P_{\text{min}}$ respectively.

### 3.3 Uniform Mutation

The role of the mutation operator is to infuse new genetic material (characteristics) into the population. With a small probability of 0.01 – 0.1, the mutation operator randomly alters the chromosomes (variable). Among the available parents, it randomly selects one of the variables $U_i$ and matches it to a random number between lower $P_{\text{min}}$ and upper $P_{\text{max}}$ limits.

### 4. RGA Implementation for Optimal Day Ahead Real Time Pricing

The proposed approach for calculating the optimal price is based on RGA. Each individual in the RGA population represents the possible solution candidate [23]. The DARTP for three different loads such as residential, commercial, and industrial loads are considered as the decision variables for the optimization problem. The upper and lower bound for the decision variable are its minimum and maximum Pricing values. As floating numbers are considered for the decision variable, the Real Coded Genetic Algorithm is deployed in the proposed approach. The steps for finding the optimal values for the profit of Energy providers using RGA are given below in a flow chart.
5. Simulation Results
The proposed DARTP scheme is implemented and the analysis was performed on the Ontario 32 node radial distribution bus, as shown in Figure 4. Loads of the distribution system are categorized based on the consumer type such as commercial, residential, and industrial as shown in Table 1. The system considered for validation is assumed to have 10 consumers in each node so that a totally 320 consumers are taken for evaluating the proposed method.
Among 32 load buses, 21 buses are considered as residential load based on their minimum energy consumption, its range varies from 0.04MW to 0.06MW. There are nine commercial loads considered and the range of its power consumption varies from 0.1 MW to 0.2 MW. There are two industrial loads and its values are 0.42 MW each.

### Table 1: Category of Loads at Different Buses of Test System

| Consumer categorization | Categorization of load bus |
|-------------------------|---------------------------|
| Residential             | 2,4,5,8,9,10,11,12,14,15,16,17,18,19,20,21,22,25,26,27,32 |
| Commercial              | 1,3,6,7,13,28,29,30,31   |
| Industrial              | 23,24                    |

### Table 2: Self and Cross Elasticity

| Type of consumer | Time duration       | Peak load period (11-17) | Intermediate-load period (7-11&17-19) | Base load period (19-7) |
|------------------|---------------------|--------------------------|----------------------------------------|--------------------------|
| Residential      | Peak load period   | -0.150                   | 0.080                                  | 0.070                    |
|                  | Intermediate-load period | 0.080                  | -0.140                                 | 0.050                    |
|                  | Base load period   | 0.070                    | 0.050                                  | -0.120                   |
| Commercial       | Peak load period   | -0.180                   | 0.070                                  | 0.050                    |
|                  | Intermediate-load period | 0.070                  | -0.170                                 | 0.030                    |
|                  | Base load period   | 0.050                    | 0.030                                  | -0.160                   |
| Industrial       | Peak load period   | -0.180                   | 0.100                                  | 0.080                    |
|                  | Intermediate-load period | 0.100                 | -0.180                                 | 0.060                    |
|                  | Base load period   | 0.080                    | 0.060                                  | -0.160                   |

The total residential load, commercial and Industrial load for 24 hours in a typical day of winter and summer are plotted as a graph in Figures 5a and 5b respectively. The DA market price for energy during a typical day of summer and winter is depicted in Figures 6a and 6b respectively. Each day is broken down into three-time intervals such as peak load period, intermediate-load period, and base load period as used in Ontario, Canada. The Peak load period is between 11-17 hours, the intermediate-load period is between 7-11 and 17-19 hours. The base load period is 19 to 7 hours.
The elasticity values at the three described time intervals for each type of user are shown in table 2. The DA energy prices and load forecasts of a typical summer and winter day are used from Ontario wholesale electricity market data to validate the effectiveness of the proposed DARTP model.

Figure 5a Daily demand curve during a typical day of winter

Figure 5b Daily demand curve during a typical day of summer
The Real coded Genetic Algorithm (RGA) is applied in the proposed work to find the optimum energy price, which is favorable for both the consumer and the energy provider. The various parameters of the RGA programming are given in Table 3. The objective of the proposed work is to maximize the profit of the energy provider. The optimization variable considered here is the DARTP of the consumer with the constraints of maintaining minimum load at all-time duration (peak load period, intermediate-load period and base load period).

Figure 6a DA market price during a typical day of winter

Figure 6b DA market price during a typical day of summer
Table 3 RGA control parameters

| Name of the parameters | Parameters value |
|------------------------|------------------|
| Number of generations  | 100              |
| Population Size        | 30               |
| No. of Variables       | 3                |
| Crossover Probability(Pc) | 0.8            |
| Mutation Probability(Pm) | 0.07          |

5.1 Case A- No RTP Participants
In this case, there are no RTP participants. The electricity rates are set by the energy provider of Ontario city as part of the Regulated Price Plan (RPP). When a customer utilizes electricity, charges incurred by the supplier will vary according to the agreement signed between supplier and consumer. In general, the energy supply costs charged to RPP customers are calculated in compliance with the rules laid down by the policy. However, large consumers pay energy rates on an hourly basis in Ontario. At the mint end adjustment of the bill occur globally for the consumers. The market price and global adjustment on an average were taken into the account to calculate the RPP. On a typical month of summer and winter, the average market prices were 3.3¢/kWh and 3.5¢/kWh respectively. The global adjustment prices were 3.5¢/kWh and 3.6¢/kWh for the above-mentioned months. Hence, the RPP prices are 6.8¢/kWh and 7.1¢/kWh considered for the month summer and winter. This RPP is assumed to be a base tariff in further cases.

5.2 Case B- Partial RTP Participants
In this scenario, two pricing concepts are used. One is DARTP price i.e., the price at that particular hour depending on the types of the time period and the second one is DA price. DA price is the sum of energy price at the respective hour and the adjustment price. It is considered that 40% of consumers are participating in the RTP program and the remaining consumers are not participating in the RTP program. The remaining 60% of consumers follow the price program as stated in Case A. Based on the DARTP price, the load is responded to the pricing program as shown in Figures 7(a) and 7(b).

![Figure 7a](image-url) Daily demand comparison curve b/n case A &B - day of winter

Figure 7a depicts the daily demand curves on a typical day of winter season. During base load hours (1-7 & 21-24), the demand closely follows the curve of Case A. During peak load hours (7-11
& 17-19) and intermediate load hours (12 -17) demand is decreased and the demand curve is shifted below the Case A curve.

Figure 7b reveals the demand curves on a typical day of the summer season. During the off-peak time (1-7) demand is increased and the demand curve is shifted above the Case A curve for which is for the no RTP participants. During peak load hours (12-17) and intermediate load hours (7 -11 & 17-19), the demand is decreased and the demand curve is shifted below the Case A curve.

![Figure 7b](image_url)

**Figure 7b** Daily demand comparison curve b/n case A &B- day of summer

Figures 7(a) and 7(b) reveals that the energy demand of consumers during peak hours will be decreased with the introduction of RTP. However, there are small load changes during off-peak hours. This is because there is minimal difference between retail prices during the day and the base energy level, which does not offer sufficient incentives for customers to adjust their demand profile.
Figures 8(a) and 8(b) show the optimal DA price during a typical day of winter and summer. Figures 8(a) and 8(b) shows the optimal real-time price presented by the energy provider. It is revealed that the energy supplier provides low energy prices during base load season to enable consumers to move part of their demand to this time. The reaction of consumers to the DARTP energy prices offered depends on their base load and on their demand elasticity, which varies for the consumers.

Table 4 lists the proposed DARTP price for the typical day of winter and summer season. During peak hours, the energy price is high to avoid peak power consumption. During the intermediate load period, the price is moderate and for off-peak, the price is low to promote consumers to move their demand to the off-peak time. Depending on the type of time-period, the consumers can shift their load since the price is announced a day ahead.
Table 4 DARTP Price

| Period            | Price /kWh (¢) | Typical day of Winter | Typical day of Summer |
|-------------------|----------------|-----------------------|-----------------------|
| Peak load period  | 9.9            |                       | 10.7                  |
| Intermediate load period | 8.1 |                     | 8.9                   |
| Base load period  | 5.1            |                       | 5.9                   |

The energy is supplied at a low cost at off-peak to encourage the customers to utilize more energy at this period. The response of consumers to the DARTP energy prices offered depends on their base consumption.

5.3 Case C- RTP Participants
In this case, all the consumers' loads are considered to take part in the RTP program. Based on the load requirement and the price, the load has participated in the RTP program actively.

The daily demand curve on a typical winter day is shown in Figure 9(a). Figure 9a reveals that the demand curve is increased during the base load period (01-07 & 21-24) and the demand curve is shifted above the Case A curve which is for the no RTP participants. During on-peak load hours (7-11 & 17-19) and intermediate load hours (12-17), demand is decreased and the demand curve is shifted below the Case A curve.

Figure 9b reveals the demand curves on a typical day of the summer season. During base load hours (1-7 & 21-24) demand is increased and the demand curve is shifted above the Case A curve which is for the no RTP participants. During peak load hours (12-17) and intermediate load hours (7-11 & 17-19), the demand is decreased and the demand curve is shifted below the case A curve.
With RTP implementation Case B has peak reduction during peak hours but still, there is a small deviation, because a small difference lies between the market price and the base energy price. Case C has a strong reduction in peak as well as a change in the load profile since all the demand was considered in participating DARTP program and the price is less. This is because the energy can be utilized at a low-cost period. In Case C, compared to Case B the displaying of ideal real-time DA prices will further minimize consumer energy consumption during peak load hours and move a greater market demand to baseload hours. However, the demand reduction is limited by the demand model equation $D_c(t)$.

The findings are analyzed economically and technically to equate the suggested DARTP model with Cases A and B. Table 5 provides technical requirements such as the reduction of peak load and load factor. From the Table, it is clear that Case C has improved load factor and improved peak reduction factor compared to Case A and Case B.

**Table 5 Technical Indicator**

|                  | Power Demand (kWh) | Peak Reduction (kW) | Load Factor (%) |
|------------------|--------------------|---------------------|-----------------|
|                  | a typical day of winter | a typical day of winter | a typical day of summer |
| Case A           | 102580             | 100310              |                 |
| Case B           | 100084             | 99780.0             | 61.72           |
|                  |                     |                     | 57.2            |
|                  |                     |                     | 0.9028          |
|                  |                     |                     | 0.8576          |
| Case C           | 99290              | 98020.0             | 274.55          |
|                  |                     |                     | 453.1           |
|                  |                     |                     | 0.9315          |
|                  |                     |                     | 0.9185          |

Table 6 indicates economic parameters are changed in Case C compared to Case A and Case B. There is a greater decrease in demand in Case C because, during peak load hour, power demand is shifted as per the intimated DARTP price. This lower price encourages the consumers to decrease their demand during peak load time as well as increasing demand in baseload time. As per the proposed model, profit is $3471.19$ and $3312.49$ on a typical day of winter and summer respectively.
### Table 6 Economical indicators

|                  | Power Demand (kWh) | Energy provider’s Profit ($) |
|------------------|--------------------|-----------------------------|
|                  | A day on winter    | A day on summer              | A day on winter | A day on summer |
| Case A           | 102580             | 100310                      | 3344.10        | 3306.30        |
| Case B           | 100084             | 99780                       | 3315.35        | 3262.10        |
| Case C           | 99290              | 98020                       | 3471.19        | 3312.49        |

6. Conclusion
Throughout this study, a new, day-to-day, RTP scheme has been introduced in the context of smart grids. By applying the suggested pricing model, each energy supplier aims to maximize the profits by offering optimum DA prices to the consumers. The market prices, consumer behavior, and distribution system data are considered as the constraints for calculating the optimal DA prices. Such calculated prices will then be sent to the consumers equipped with an advanced metering system available at the consumer end. The developed DARTP model has been validated with a 32-node distribution system. A total number of 320 are taken into the account along with their demand, market curves, and regular price tariffs of Ontario City. The simulation results demonstrate that the use of the DARTP model results in a flatter demand curve, minimum losses, higher load factor. This RGA-based DARTP pricing model offers a chance to make better use of the advantages of smart grids in the distribution network.

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