MULTI-OBJECTIVE CONGESTION MANAGEMENT OF TRANSMISSION LINES USING DEMAND RESPONSE AND STATIC VAR COMPENSATORS

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Abstract*: This paper presents multi-objective congestion management of transmission lines using time-of-use (TOU) based demand response (DR) program and static var compensator (SVC). Congestion of transmission lines is managed, while system parameters such as generation fuel cost and active power losses are reduced, in addition to enhancement of bus voltages. The SVC was modeled as a reactive power injector***,** *while the TOU-based DR was modelled using the price elasticity of demand for responsive loads. Particle swarm optimization was used for the optimal placement and sizing of the SVCs***,** *considering the rolled-out DR program in MATLAB/MATPOWER. The DR program was first tested separately on the IEEE-30 bus test system to show its effects on the afore-mentioned system parameters. Subsequently, the DR program was combined with the SVC, and again tested on the IEEE-30 bus test system. The results showed a significant improvement of 1.414% on the voltage profile, 44.65% reduction on the generation fuel cost, and much significant 71.13% reduction on the system losses with the proposed method, compared with the Base Case Scenario (the Peak Period) where there was congestion. This shows the effectiveness of the proposed hybridized DR-SVC method in congestion management of transmission lines.*

1. INTRODUCTION

Traditionally, electric grids were designed to operate as a vertical structure consisting of generation, transmission, and distribution, supported with controls and devices to maintain reliability, stability, and efficiency. Generation companies enjoyed monopoly by operating the whole vertical structure. Now, the increase in demand in the electric power systems has necessitated the restructuring of the power system, even as more generators are required, resulting in a market-based competition by creating an open market environment which allows the power supply to function competitively, as well as allowing consumers to choose their own suppliers of electric energy [1].

The restructuring has moved the electric grid from a highly regulated, vertical structure to a fully unbundled structure referred to as power sector deregulation. The principal aim of deregulation is to create the avenue for more generation from independent power producers (IPPs), enhance the existing efficiency, reliability, and security, as well as reduce the cost of producing and using energy by introducing competition in the power industry [2].

Increased demand for energy in a deregulated power system has also resulted in an increase in the number of power producers, whilst consumers have the liberty to choose their own generating companies. Ordinarily, increase in demand with its associated increase in generation should result in an increase in the number of transmission lines. However, as a result of environmental concerns, right-of-way issues, and increased cost of construction of lines, amongst others, there is an increasing recognition of an absolute necessity to utilize the existing transmission systems' assets to the maximum extent as possible. But increasing energy demand creates constraints in the power transmission system, as more generators are added, and the existing lines are forced to carry power beyond their limits [3], [4]. This situation has resulted in congestion of the existing transmission lines and leads to violations of transmission constraints, leading to an increase in transmission losses and generation fuel cost. This is inimical to the transmission system and optimal power flow, and as a result, this congestion must be managed [3].

A number of measures have been adopted to address the issue of transmission congestion. Each of these methods has different effects on the generation fuel cost, system losses and the voltage profile. Some of these methods include demand response (DR), generator rescheduling, load shedding, distributed generations, nodal pricing schemes, operation of transformer taps, operation of Flexible Alternating Current Transmission System (FACTS) devices and so forth [5], [6], [7].

Singh and Kumar [8], modelled the Time-Of-Use (TOU) and the Emergency Demand Response Program (EDRP) using the responsive load model and price elasticity of demand in congestion management. The models of both DR programs were tested on the IEEE 24-bus reliability test system using MATLAB. The incentives considered for the EDRP were 10 $/MWh, 25 $/MWh, and 35 $/MWh. This work, however, does not consider the uncertainty nature of the load and the customers. The uncertainty nature of the DR responsive load, a demerit of the DRPs, has to do with the fact that customers can choose whether or not to participate in the DRP when used as the sole congestion management tool, leading to a jeopardy of the program at times (an effect of this uncertainty).

Also, Luo et al. [9] worked on minimizing this uncertainty nature associated with the DR responsive load in congestion management. The authors proposed a Consensus-based Nodal Pricing Mechanism for Automated Demand Response by using automated DR devices.

These automated DR devices are smart breakers and telemetry devices which trip off to cut the load on which they are placed when their preset times are reached. This method minimizes the uncertainty and its effect to some extent, because customers who decide to participate in the Automated DR program will not be able to leave the program along the way, as these timed-preset automatic tripping devices will be installed on their loads. However, customers can still decide from the beginning not to participate in the program and will have no automated device installed on their load. Secondly, the application is expensive, as these automated devices are costly. Thirdly, the application involves a two-way communication infrastructure in the grid, and so not all grids will be capable of implementing this approach. A relatively more inclusive and less expensive remedy to minimize this uncertainty and its effect, is the proposed combination of the DRP approach with another congestion management tool, say SVC FACTS device, to obtain a hybridized congestion management approach. With the application of the SVC, the voltage profile will still be enhanced, even if the customers decide no more to participate in the DRP or abandon the program along the way, thereby eliminating or reducing the effect of the uncertainty.

Nandini et al. [10] and Yousefi et al. [11] worked on congestion management using both demand response and FACTS devices. Their works considered the uncertainty nature of the responsive load by adding FACTS devices. The demerits are that these works failed to consider cross-elasticity (flexible load model) in the price elasticity of demand model. The non-inclusion of the flexible load (cross-elasticity) model in the DR responsive load modelling means that only fixed loads (like lights, television sets, etc.) were considered in the DR responsive load modelling. But this should not be the case, because the customer's load of a real-world power grid (real-world load) is a combination of both fixed loads (lights, TV sets etc.) and flexible loads (like heating, ventilation and air conditioning (HVAC) equipment, electric vehicle, etc.). Hence the non-inclusion of the flexible load model makes that modelling of the customer's load incomplete, and it does not represent the load of a real-world power grid. Therefore, in this paper, the flexible load model (cross-elasticity) has been factored in the modelling of a real-world DR responsive load, and its effects in congestion management analyzed. Additionally, when only the demand was optimized (single-objective function approach), without considering voltage and fuel cost**,** it resulted in voltage constraint issues at Bus 29. Hence two or more parameters must be optimized at the same time (the multi-objective functionality approach).

This paper therefore considers congestion management using a multi-objective approach, where some key grid parameters are optimized simultaneously, producing effects and results far better than the single-objective function approach. A combined application of demand response program (DRP) and static var compensator (SVC) FACTS devices was adopted, and the resulting effects on the generation fuel cost and system losses, as well as voltage profile of the system analyzed. The TOU demand response program was modeled based on price elasticity of demand (PED) for responsive loads including the flexible load model, and used in conjunction with the SVC modelled as a reactive power injector operating as a variable susceptance. The effects of this hybridized DRP-SVC approach were explored on the IEEE 30-bus test system using the particle swarm optimization (PSO) tool to optimally size and place the SVC using the MATLAB/MATPOWER simulation environment.

2. THEORITICAL CONSIDERATIONS

2.1. Transmission congestion and its effects

Transmission congestion refers to situations when transmission constraints limit transmission flows or throughput below levels desired by market participants or government policy in order to comply with reliability rules. Transmission congestion occurs as a result of transmission constraints – a lack of transmission line capacity to deliver electricity without exceeding thermal, voltage and stability limits designed to ensure reliability [12]. Congestion arises when there is a desire to increase throughput across a transmission path, but such higher utilization is thwarted by one or more constraints. Congestion management in transmission system refers to any strategy or group of strategies focused on avoiding, reducing, or eliminating congestion in the transmission system as well as its consequences on the transmission grid. It is a process of performing the task of prioritizing the transactions and making such a schedule which solves the problem of overloading the network [13].

When thermal, voltage or stability limits are violated in a transmission network, congestion is said to have occurred and available electricity supply is not delivered at low cost to the load which, and as a result, defeats the intention of deregulation [14]. Congestion in power system makes the system unsecure with hikes in power prices due to avoidable losses, as it jeopardizes optimal power flow (OPF) [15]. Additionally, congestion maximizes the cost objective function by increasing the cost of generation and marginal costs at the buses. This situation increases the amount that the consumer pays as the cost of energy [16]. In [13], the relevance of congestion management is discussed in detail by identifying congestion management as one of the key issues to maintain security and reliability of transmission networks. Furthermore, congestion management balances the system and solves financial issues arising from the inability of the network to deliver the demanded power. The finding in [5] further stipulates that, lack of attention to congestion in the system may lead to widespread blackouts, and the associated negative social and economic consequences.

2.2. Demand response

According to the Federal Energy Regulatory Commission (FERC), demand response (DR) is defined as: “changes in electric energy usage by end-use customers from their normal consumption patterns, in response to changes in the price of electricity over time, or incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is likely to be jeopardized." [17]. Demand response is a wide range of actions which can be taken at the customer side of the electricity meter, in response to particular conditions within the electricity system (such as peak period network congestion or high prices). Demand response program furthermore plays a vital role in a smart grid environment, as it is an economical and flexible attempt towards the maintenance of system security and reliability, and also creates opportunities for customers to also be players in the market [14]. As a result, DR programs demand a two-way communication in the grid. However, DR has a limited capability, as it totally depends on the effective participation of customers from time to time. The consumer may fail to reduce their load due to some external factors, and this sometimes jeopardizes the effectiveness of the program in the congestion management. This kind of situation is referred to as the uncertainty nature of the responsive load or the consumers.

Demand response is able to change the amount and duration of electric energy usage, so that the best efficiency of consumption takes place in the peak interval [18]. Demand response programs are categorized as incentive-based (IB) or time-based (TB) programs. The IB programs are further divided into direct load control (DLC), interruptible/curtailable (I/C) service, demand bidding/buy back, emergency demand response program (EDRP), capacity market program (CMP) and ancillary service (A/S) markets. The TB programs, on the other hand, are further grouped as time-of-use (TOU), real time pricing (RTP) and critical peak pricing (CPP) programs [19], [20].

2.3. Economic model of responsive load

During the early years of deregulation of the power sector, consumers were fundamentally not participating effectively in the power markets [19]. As a result, consumers were isolated from any information of the markets, and did not enjoy the benefits either. This was basically as a result of the absence of knowledge, proper hardware, and infrastructure to aid the participation of the consumers in the power markets. The absence of consumer participation in the power markets resulted in price spikes, and also caused the transmission system to be congested [21].

The economic model of the responsive load is based on price elasticity of demand (PED). The demand for most commodities decreases as their prices increase. Price elasticity of demand or simply elasticity (E) is defined as the sensitivity of demand in respect of the price [22]. Mathematically, the elasticity E is expressed as [8], [14] and [22]:

$$E = \frac{\partial q}{\partial \rho} \tag{1}$$

where, E is elasticity of demand, q is demand value in respect to a period (MW), and ρ is electricity price in respect to a period ($/MWh).

As is the case for the TOU program, there are three prices periods with different prices variations. Also, the demand is one or both of the following:

1. *Fixed loads* – These are the loads that are not able to move or be shifted from one period to another. Examples are illuminating loads (lights), television sets, and so on. They could only be either 'on' or 'off', and so such loads have a *sensitivity* just in a *single period*, called *self-elasticity* [22] and it always has a *negative value*.
2. *Flexible loads* - These are the loads that could be shifted or transferred from one period to the other, say, from the peak period to the off-peak or to the flat period. Examples are heating, ventilation and air-conditioning (HVAC) equipment, electric vehicles (EV) and so on. Such loads have sensitivity in *multi periods* and evaluation is done by *cross-elasticity* [22]. This always denotes a *positive value*.

From (1), self-elasticities and cross-elasticities are suitably expressed according to [8], [14], [22] as:

$$E_{ii} = \frac{\Delta q_i}{\Delta \rho_i} \leq 0 \tag{2}$$

$$E_{ij} = \frac{\Delta q_i}{\Delta \rho_j} \geq \tag{3}$$

where Δq_i is the change in demand in i-th hour in a period, $\Delta \rho_i$ is the change in price in i-th hour in the same period and $\Delta \rho_j$ is the changes in price in j-th hour in another period. E_{ii} and E_{ij} are respectively self- and cross- elasticities. Both E_{ii} and E_{ij} for a 24-hour TOU program divided into 24 slots of one hour are 24x24 matrix called price elasticity matrix of demand (PEMD) with E_{ii} having only its diagonal values being non-zero (all other values of the matrix are zero) [23], [24].

The adopted TOU program is modelled using PED to show its effects on the electricity/power markets demands and prices, and also to show how beneficial this is to customers when they follow the program. This is done using both the single and multi periods models. Concerning the adopted model for the TOU program in this paper, the 24-hour day was divided into one-hour slots of twenty-four, i.e., 1, 2, 3, …, 24, and further grouped into three periods, namely; peak, flat and valley periods.

The Valley Period has comparatively the *lowest power (energy demand)*. In this period, congestion does not occur, and locational marginal prices (LMPs) are at their lowest. The utilities then set the energy prices at the lowest as a result of the afore-mentioned conditions [19], [25]. The Flat Period is the longest period by duration. A chunk of the power (energy) demand in this period is a combination of industrial, commercial and residential. In most of the time, bulk customers install static capacitors and other FACTS devices to help boost their voltage and power factor. As a result, the energy demand during this period is not as high as the Peak Period, and not as low as the Valley Period with its matching tariff set by the utilities [19], [25]. The Peak Period is the period during which the energy demand is the highest. The demand in this period is mostly residential, when most of the consumers have closed from work, preparing for the next day activities, charging their battery-drained electric vehicles, operating their HVAC systems and so forth. However, some of the demand here could also be from the commercial and industrial customers who do shift operations. As a result, the lines become loaded, leading to congestion. The LMPs increase and utilities set their tariffs at the highest [19], [20], [25].

i. Single-Period Model (For Fixed Load. e.g., Lights, TV sets etc.)

Consider the following electricity market parameters for the customer:

d(i) = Customer's demand in *i*-th hour (MWh).

ρ(i) = Electricity price in *i*-th hour ($/MWh).

C(i) = Customer's income in *i*-th hour readily available to follow program ($).

Now, let us suppose that the customer changes their demand value from an initial value of $d_0(i)$ to a final value of *d(i)* due to the spot electricity price in the *i*-th hour (*i*) , then we can express the change in demand Δ*d(i)* as:

$$\Delta d(i) = d(i) - do(i) \tag{4}$$

Hence, the customer's balance *M($)* in the *i*-th hour for running the TOU program will be:

$$M(d(i)) = C(d(i)) - \Delta d(i).\rho(i) \ \ (\$) \tag{5}$$

$$M(d(i)) = C(d(i)) - \rho(i).[d(i) - do\ (i)] \ \ (\$) \tag{6}$$

$$M(d(i)) = C(d(i)) - \rho(i)d(i) + \rho(i)\ do\ (i) \ \ (\$) \tag{7}$$

In order to maximize the customer's benefit, the partial differential of *M* with respect to *d(i)*, that is, $\left(\frac{\partial M(d(i))}{\partial d(i)}\right)$ should be zero.

Hence:

$$\frac{\partial M(d(i))}{\partial d(i)} = \frac{\partial C(d(i))}{\partial d(i)} - \rho(i) + \frac{\partial \rho(i) d_o(i)}{\partial d(i)} = 0 \tag{8}$$

Therefore,

$$\frac{\partial C(d(i))}{\partial d(i)} = \rho(i) \tag{9}$$

According to [19], [26], and [27], the customer's benefit, being a function of the customer's income, which is more appropriate and most of the time used, is a quadratic function and can be expressed as:

$$C\big(d(i)\big) = C_o(i) + \rho_o(i).[d(i) - d_o(i)].\left\{1 + \frac{(d(i)-d_o(i)}{2E(i).d_o(i)}\right\} \tag{10}$$

where $C_o(i)$ is the benefit when the demand is at its nominal or initial value of $d_o(i)$, and $\rho_o(i)$ is the initial spot electricity price when the demand is still at its nominal value.

Taking the partial derivative of (10) results in;

$$\frac{\partial C(d(i))}{\partial d(i)} = \rho_o(i) + \rho_o(i).\left\{\frac{(d(i)-d_o(i)}{E(i).d_o(i)}\right\} \tag{11}$$

$$\frac{\partial C(d(i))}{\partial d(i)} = \rho_o(i).\left\{1 + \frac{(d(i)-d_o(i)}{E(i).d_o(i)}\right\} \tag{12}$$

Considering (9) and (12),

$$\rho(i) = \rho_o(i).\left\{1 + \frac{(d(i)-d_o(i)}{E(i).d_o(i)}\right\} \tag{13}$$

By rearranging;

$$\rho(i) - \rho_o(i) = \rho_o(i).\frac{d(i)-d_o(i)}{E(i).d_o(i)} \tag{14}$$

$$d(i) - d_o(i) = E(i).d_o(i)\ \frac{\rho(i)-\rho_o(i)}{\rho_o(i)} \tag{15}$$

$$d_s(i) = d_o(i).\left\{1 + E(i).\frac{\rho(i)-\rho_o(i)}{\rho_o(i)}\right\} \tag{16}$$

Therefore, by further rearranging (16), the customer's consumption for the single-period model will be as:

$$d_s(i) = d_o(i).\left\{1 + E(i).\frac{\rho(i)-\rho_o(i)}{\rho_o(i)}\right\} \tag{17}$$

where $E(i)$ is the self-elasticity of demand as described above. It can, however, be realized in

(17) that, if there is no prize change from one period to the other, and that the price of electricity remains constant throughout the day (24 hours). Then the term $\rho(i) - \rho_o(i)$ will be equal to zero ($\rho(i) - \rho_o(i) = 0$), rendering the elasticity *E(i)* zero, and as a result, *d(i)* will be equal to $d_o(i)$. Thus, there will be no change in demand in respect to a change in price, as there will be no change in price, resulting in zero elasticity.

ii. Multi-Period Model (For Flexible Load. e.g., HVAC, EV, etc.)

According to [19] and [28], the cross-elasticity between the demand in the *i*-th hour and the price in the *j*-th hour can be expressed as:

$$E(i,j) = \frac{\rho_o(j)}{d_o(i)}\ x\ \frac{\partial d(i)}{\partial \rho(j)} \tag{18}$$

such that $E(i,j) \le 0\ if\ i = j$ and $E(i,j) \ge 0\ if\ i \ne j$.

From the basis that the demand's response to price variations can be expressed as a linear function [28], and considering (18), let us suppose that $\partial d(i)/\partial \rho(j)$ is constant. This means that, for every change in electricity price in *j*-th hour in a particular period, there will be a corresponding change in demand in the *i*-th hour in another period with its associated cross-elasticity. Hence from (14);

$$\rho(j) - \rho_o(j) = \rho_o(j). \frac{d(i) - d_o(i)}{E(i,j).d_o(i)} \tag{19}$$

In cross-elasticity, every single demand in the *i*-th hour over the 24-hour day is influenced by all the prices variations in the *j*-th hour over the 24-hour day. Therefore;

$$d(i) - d_o(i) = \sum_{j=1}^{24} E(i,j).\, d_o(i) \left\{\frac{\rho(j) - \rho_o(j)}{\rho_o(j)}\right\} \tag{20}$$

$i = 1, 2, 3, \dots \dots 24$ and $j = 1, 2, 3, \dots \dots 24$

Hence, the customer's demand function considering the multi-period model is:

$$d_m(i) = d_o(i) + \sum_{j=1}^{24} E(i,j).\, d_o(i) \left\{\frac{\rho(j) - \rho_o(j)}{\rho_o(j)}\right\} \tag{21}$$

$i = 1, 2, 3, \dots \dots 24$ and $j = 1, 2, 3, \dots \dots 24$

iii. Final Demand Model (For both Fixed and Flexible Loads)

According to [19], [26], [27], and [29], the final demand model will be a combination of the single period and multi-period demand, (17) and (21), respectively. As already mentioned, the day is grouped into three periods under the TOU program in this work. The advantage of the TOU program over the RTP program is that, the former offers simple computations compared to the latter where the day is divided into many slots, usually 24 one-hour slots. This means that within the same period in a TOU program, irrespective of the duration of the period, the price remains the same. As a result, the customer's Final Demand equation $d_f(i)$ is expressed as:

$$d_f(i) = d_m(i) \,.\frac{d_s(i)}{d_o(i)} \tag{22}$$

Since there is self-elasticity in the same period and there is no change in price, there is no change in demand and so the term $d_s(i)/d_o(i)$ is always equal to unity ($d_s(i) = d_o(i)$) in the same period. This means that in the same period, $d_f(i) = d_s(i) = d_m(i)$ and therefore the expression for $d_f(i)$ is justifiably valid. Hence:

$$d_f(i) = \{d_o(i) + \sum_{j=1}^{24} E(i,j).\, d_o(i)[\frac{\rho(j)-\rho_o(j)}{\rho_o(j)}]\} \,.\{1 + E(i).\,[\frac{\rho(i)-\rho_o(i)}{\rho_o(i)}]\} \tag{23}$$

This is the customer's final demand or consumption for each hour of the day (24 hours). Equation (23) is seen to take into consideration both self-elasticities and cross-elasticities, that is, it factors both fixed and flexible loads (loads of a real-world system).

2.4. Model of the static var compensator

The SVC is a shunt static VAR generator or load whose output is arranged to switch and inject or consume either a capacitive or inductive current depending on the nature of the system's load, so as to vary power system parameters, in particular bus voltage and power factor [30], [31], [32]. When the bus at which the SVC is connected has a low voltage level, SVC injects reactive power (capacitive) to the bus. On the other hand, when the bus voltage level is high, SVC absorbs reactive power (inductive) from the bus. Typically, an SVC comprises one or more banks of fixed or switched shunt capacitors or reactors, of which at least one bank is switched by thyristors. Elements which may be used to make an SVC typically include:

- Thyristor controlled reactor (TCR), where the reactor may be air-cored or iron-cored.
- Thyristor switched capacitor (TSC).
- Harmonic filter(s).

- Mechanically switched capacitors or reactors (switched by a circuit breaker).

Figure 1 shows a schematic representation of an SVC.

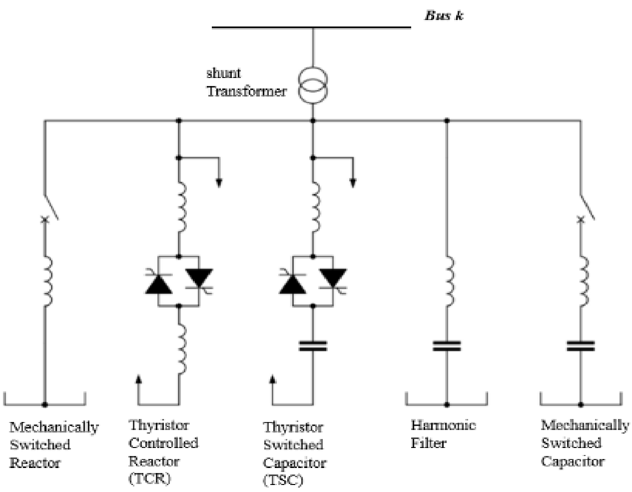

Fig. 1. Schematic diagram of an SVC [31], [33]

The structure of the static model of the SVC is a combination of a capacitor bank, shunted by a thyristor-controlled reactor with the whole connected in shunt to bus k as represented in *Fig. 2* where I_{SVC} and V_k are the injected current by the SVC and the bus voltage at bus *k*, respectively.

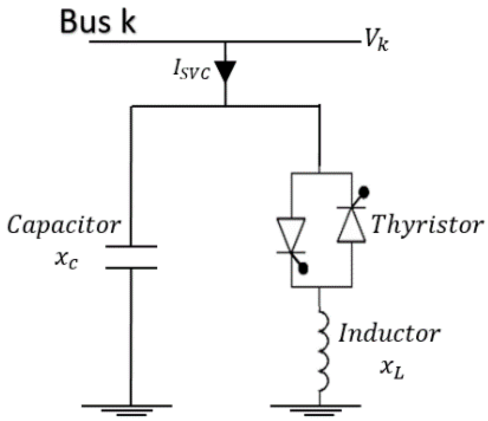

Fig. 2. Structure of the static model of the SVC [33], [34]

This static model is summarized and represented as a variable shunt susceptance B_{SVC}, shown in *Fig.3*.

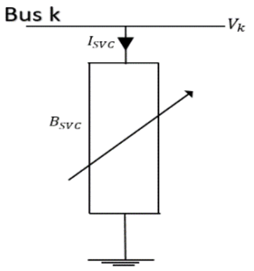

Fig. 3: Variable shunt susceptance model of the SVC [31], [34]

The injected reactive power Q_{SVC} at bus k by the SVC is expressed as:

$$Q_{SVC} = -V_k^2 * B_{SVC} \tag{24}$$

The linearized power flow models make use of (24) to make modifications in the corresponding Jacobian elements at the SVC bus. By considering the SVC's susceptance as a control variable, the load flow model of the SVC can always be developed.

2.5. Problem formulation

In this section, the mathematical concepts of the multi-objective approach are presented. The two objective functions to be considered here are generation (fuel) cost minimization and line active power losses minimization.

- *Generation fuel cost minimization*

This objective seeks to dispatch the generation such that priority is given to generators with very affordable fuel cost, and also to optimize the active power outputs of the generators. The optimization problem can therefore be formulated as [35]:

$$\text{Min } \sum_{i=1}^{nG} CPG_i \quad (\$/hr) \tag{25}$$

where *nG* is the number of generators, *CPG* is the cost of active power generation. *CPG* is often a polynomial function and can be expressed mathematically as [35]:

$$CPG_i = a_i PG_i^2 + b_i PG_i + c \;\; (\$/hr) \tag{26}$$

with a_i, b_i, c_i and PG_i being the generation coefficients of the *i*-th generator and the active power generated by the *i*-th generator, respectively.

- *Line active power losses minimization*

This objective seeks to achieve an optimal match of the active power generation with the active power demand (load) in the system. It optimizes the active power output of the slack bus and seeks to reduce the difference between generation and demand as far as active power is concerned, thus, minimizing the line losses. The optimization problem can be formulated as [35]:

$$\text{Min} \ \left(\sum_{i=1}^{nG} PG_i - \sum_{k=1}^{nD} PD_k\right) \tag{27}$$

where PG_i and PD_k are the active power generated by the i-th generator and the active power demanded at the k-th bus respectively, nG and nD are the number of generators and the number of active power demand buses, respectively.

- *Optimization problem constraints*

The above problems that have been formulated are all subject to load flow equality and inequality constraints expressed below. The equality constraints are both the balanced active and reactive power flow equations of the system. The various equations can be expressed as:

Load flow equations without FACTS devices.

$$PG_i - PD_i = |V_i| \sum_{j=1}^{nBUS} |V_j| \, |Y_{ij}| \cos(\theta_{ij} + \delta_j - \delta_i) \tag{28}$$

$$QG_i - QD_i = -|V_i| \sum_{j=1}^{nBUS} |V_j| \, |Y_{ij}| \sin(\theta_{ij} + \delta_j - \delta_i) \tag{29}$$

where PG_i, PD_i, QG_i, and QD_i are the active power generated, active power demanded, reactive power generated, and reactive power demanded at bus i, respectively. V_i, V_j, Y_{ij}, θ_{ij}, δ_i, and δ_j are respectively the i-th bus voltage magnitude, the j-th bus voltage magnitude, the branch admittance magnitude between the i-th bus and the j-th bus, the branch admittance phase angle between the i-th and the j-th bus, the voltage angle of the i-th bus and the voltage angle of the j-th bus. $nBUS$ is the number of buses.

Load flow equation with SVC placed at bus k.

$$QG_k - QD_k = -(|V_k| \sum_{j=1}^{nBUS} |V_j| \, |Y_{ij}| \sin(\theta_{ij} + \delta_j - \delta_i) + V_k^2 B_{SVC}) \tag{30}$$

The inequality constraints are the system operating limits. They are expressed as follows:

A*ctive and reactive power generation limits:*

$$PG_i^{min} \leq PG_i \leq PG_i^{max} \qquad for\ i = 1, \dots \dots, nG \tag{31}$$

$$QG_i^{min} \leq QG_i \leq QG_i^{max} \qquad for\ i = 1, \dots \dots, nG \tag{32}$$

The MVA flow limits in the branches denoted by:

$$|S_i(\theta, V)| \leq S_i^{max} \qquad for\ i = 1, \dots \dots, nBr \tag{33}$$

Bus voltage limits:

$$V_i^{min} \leq V_i \leq V_i^{max} \qquad for\ i = 1, \dots \dots, nBUS \tag{34}$$

SVC susceptance limit:

$$B_{SVC}^{mim} \leq B_{SVC} \leq B_{SVC}^{max} \tag{35}$$

2.6. Particle swarm optimization (PSO)

Particle swarm optimization (PSO) is a heuristic method that optimizes a problem by trying to improve a candidate's solution iteratively. It is a population-based search algorithm in which individuals, referred to as particles, change their positions in a seacrh-space in serach for a global best position called G_{best} [31], [34]. Each particle moves by its own experience and cognitive, taking cognizance of its environment/neighborhood, using its velocity. This particle's movement in the search-space is therefore influenced by its local best-known position called P_{best}, while it is also guided toward the best-known positions in the search-space which are updated as other particles find better positions. The P_{best} is an evaluted fitness value of the particle. The particle's velocity and position are updated at every iteration, until the maximum number of iterations T_{max} which is a major stopping criterion that is reached by (36) and (37) below. These are the main equations of the PSO algorithm.

$$v_{id}(t+1) = wv_{id}(t) + c_1r_1\big(p_{id} - x_{id}(t)\big) + c_2r_2\left(p_{gd} - x_{id}(t)\right) \tag{36}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{37}$$

where $x_{id}(t)$ is the current position of the particle i, p_{id} is a better position of particle i, p_{gd} is the entire swarm's better-known position, w is the inertia factor (positive constant), c_1 and c_2 are also positive constants called cognitive learning rate, r_1 and r_2 are randomly generated numbers ranging between 0 and 1, and v_{id} is the velocity of the particle belonging to the range of minimum and maximum velocities V_{min} and V_{max}.

3. PROPOSED METHOD

Towards the execution of the research work, the following methodological steps were followed:

1. The TOU demand response program was modeled based on price elasticity of demand (PED) for responsive loads including the flexible load model.
2. The SVC was modelled as a reactive power injector operating as a variable susceptance.
3. The standard IEEE 30-bus test system was selected as the case-study system, and simulated using the MATLAB/MATPOWER.
4. The DR (TOU) program was applied solely on the case-study system, and the multi-objective effects on congestion noted.
5. The DRP was then used in conjunction with the SVC, which was optimally sized and placed using the particle swarm optimization (PSO) tool, and again applied to the case-study system.
6. The multi-objective effects of this hybridized DRP-SVC approach on the IEEE 30-bus test system were also noted, and then compared with those of the DRP (TOU) approach.

3.1. Study system

The case study system is the standard IEEE 30-bus test system, which is represented in *Fig. 4*.

The generators' data for this standard test system above is shown in Table 1 [37].

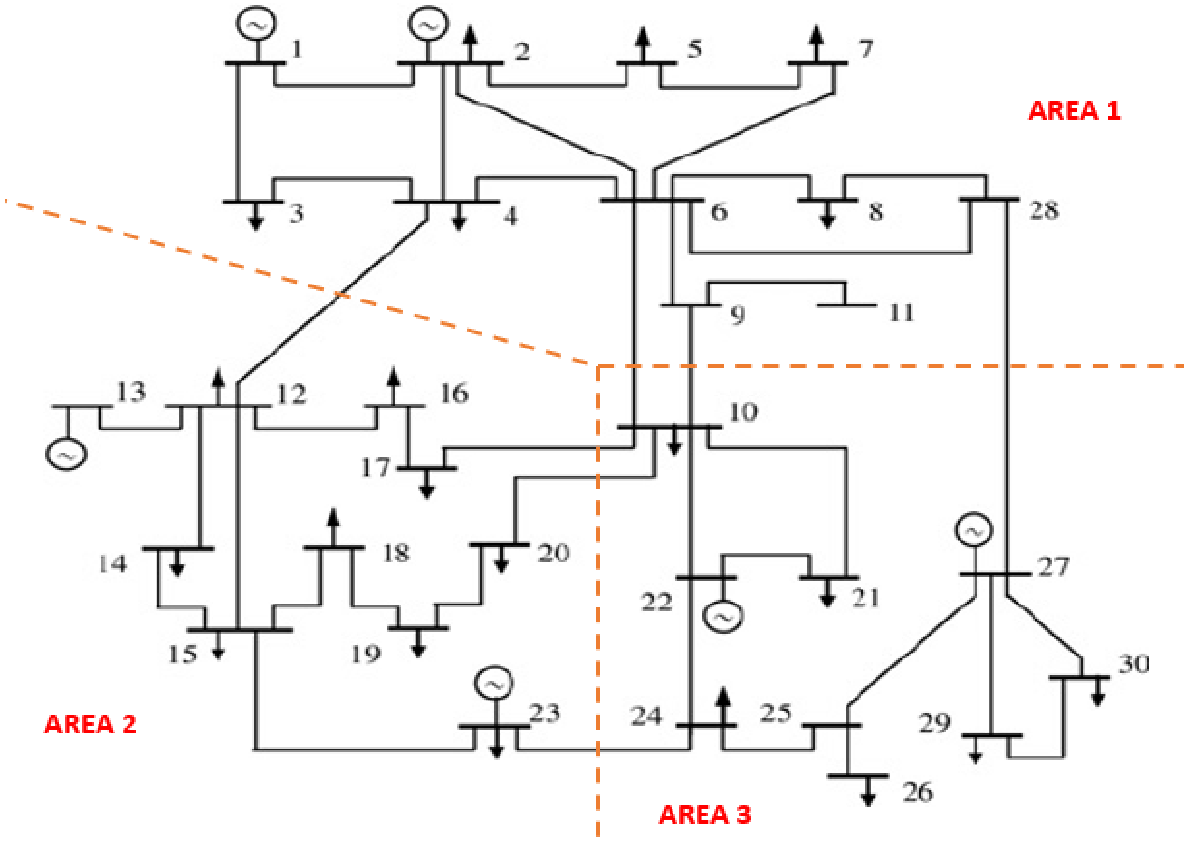

Figure 4: IEEE 30-bus test system [36]

Table 1. Generator data – IEEE 30-bus test system

Gen. no.	*Bus no.*	*Pmin (MW)*	*Pmax (MW)*	*ai ($/MW²hr)*	*bi ($/MWhr)*	*ci ($/hr)*
1	*1*	*0.00*	*80.00*	*0.02000*	*2.00*	*0.00*
2	*2*	*0.00*	*80.00*	*0.01750*	*1.75*	*0.00*
3	*22*	*0.00*	*50.00*	*0.06250*	*1.00*	*0.00*
4	*27*	*0.00*	*55.00*	*0.00834*	*3.25*	*0.00*
5	*23*	*0.00*	*30.00*	*0.02500*	*3.00*	*0.00*
6	*13*	*0.00*	*40.00*	*0.02500*	*3.00*	*0.01*

3.2. Implementation of the PSO

The PSO was used to resize and locate the already sized (with the presence of DRP) SVC in the IEEE 30-bus test system considering the objective functions of voltage profile, generator fuel cost, system losses and demand. The algorithm was used to combine the DRP and the SVC FACTS device as a single hybridized congestion relieving program. In this application, three cases were considered. These are:

- Case 1 ('the Base Case or Reference Scenario') represents the Peak Period conditions.
- Case 2 ('with DRP only') represents the sole application of the DRP on the same case study system, and
- Case 3 ('with both DRP and SVC') represents the combination of the DRP and SVC FACTS device.

The implementation of the PSO was done according to the following steps:

- *Step 1-Setting of Network Parameters:* The IEEE 30-bus network data including the reactive power and voltage constraints were read and set. The bus data was replaced with bus data obtained from the results of the application of the DRP on the IEEE 30 bus system. This afore-mentioned data was used to compose the power flow algorithm where the locations, sizes, and limits of SVC were randomly picked, arranged, and set.
- *Step 2-Particle Parameters and Initialization*: The number of particles *NP*, accelerate constants C_1 and C_2, the minimum and maximum inertia weights W_{min} and W_{max}, as well as the maximum iteration number T_{max} were set. Subsequently, the position and velocity of the particle were randomly initialized.
- *Step 3-Fitness Evaluation*: The fitness of the particles of the swarm was evaluated according to the fitness function to obtain the P_{best} and the G_{best} and the particle's velocity was set at zero.
- *Step 4-Weight Inertia Determination and Velocity Updates*: While the maximum number of iterations T_{max} has not been reached by the iteration counter (t) and the counter variable (i) not exceeding the number of particles *NP*, determine the particle's weight inertia using equation

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{T_{max}}\right) * \mathrm{t} \tag{38}$$

  and subsequently update the particle's velocity using (36).
- *Step 5-Position Updates*: In accordance with the new velocity, the particle's new position is also updated using (37). If any particle violates its position limit, the position is reset at the violating limit.
- *Step 6-Update P_{best} and G_{best}*: The fitness of all the particles in the swarm is re-evaluated with the new positions to obtain the new P_{best} and G_{best}. The location of the SVC is indicated by the particle's position with an appropriate size considering the voltage of that position.
- *Step 7-Termination:* The termination criterion was based on the preset maximum number of iterations T_{max}.

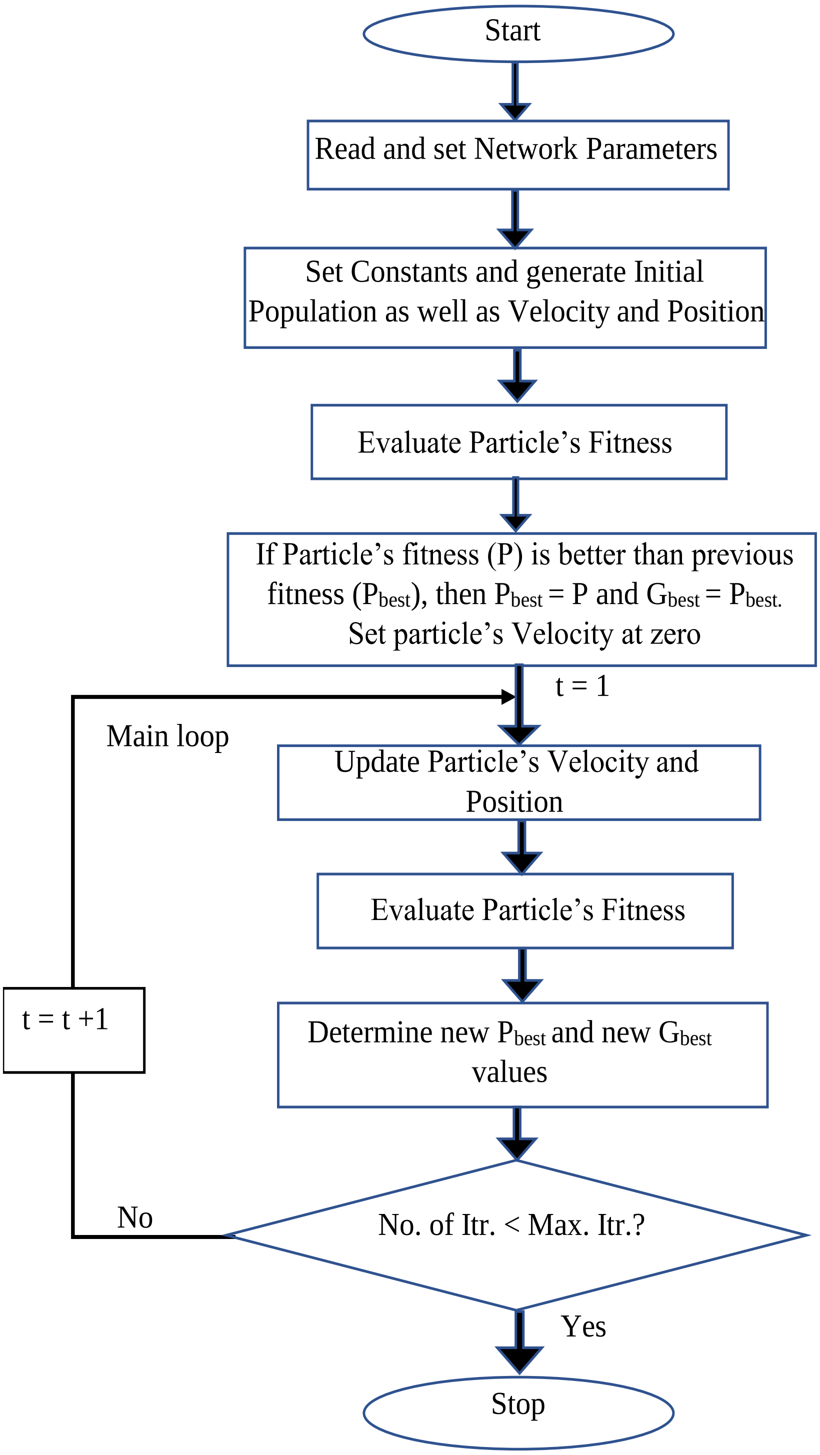

Fig.5. Flowchart of used PSO Algorithm

The flowchart is shown in *Fig. 5*.

4. RESULTS AND ANALYSIS

The PSO control variables or parameters used are:
Number of Particles (NP) = 50
Maximum number of iterations T_{max} = 100
Minimum inertia weight W_{min} = 0.4
Maximum inertia weight W_{max} = 0.9
Accelerate constants $C_1 = C_2 = 2$.

The PSO algorithm optimally placed two SVCs of sizes 15.33 MVar and 10.71 MVar at buses 8 and 21, respectively. Table 2 is a snapshot from the MATLAB command window showing the placed and sized SVCs by the PSO.

Table 2. Snapshot from the results of the PSO-based sizing and placing of the SVCs

```
t = 95 BEST = 46247.5268
t = 96 BEST = 46247.5268
t = 97 BEST = 46247.5268
t = 98 BEST = 46247.5267
t = 99 BEST = 46247.5266
t = 100 BEST = 46247.5265
=====================================================
Buses are   4   5   2  19  17  22  24  23  20  18  21    25   26   9   8   11   27
sizes are   0   0   0   0   0   0   0   0   0   0  10.71  0    0   0  15.33  0   0

        Buses     Size(MVAr)
          8         15.33

         21         10.71

=======================================================
```

The results have been presented for the three cases, namely: Case 1 - the Base Case Scenario, Case 2 - with DRP only, and Case 3 - with both DRP and SVC, as follows.

4.1 Effects on the Voltage Profile

Table 3 and *Fig. 6* present the 30 voltage profiles for all the three cases.

Table 3. Voltage profiles for all the three cases

	Voltage Profile				
Bus Number	***Case 1 (Base Case Scenario)***	***Case 2 (With DRP Only)***		***Case 3 (With DRP and SVC)***	
		In p.u.	***% Increase***	***In p.u.***	***% Increase***
1	*1.050*	*1.050*	*0.000*	*1.050*	*0.000*
2	*1.013*	*1.017*	*0.395*	*1.024*	*1.086*
3	*1.000*	*1.011*	*1.100*	*1.027*	*2.700*
4	*0.981*	*1.001*	*2.039*	*1.012*	*3.160*
5	*0.979*	*0.985*	*0.613*	*0.992*	*1.328*
6	*0.972*	*0.981*	*0.926*	*0.988*	*1.646*
7	*0.976*	*0.984*	*0.820*	*0.990*	*1.434*
8	*0.979*	*0.985*	*0.922*	*1.008*	*3.279*
9	*1.015*	*1.022*	*0.690*	*1.031*	*1.576*
10	*1.012*	*1.019*	*0.692*	*1.025*	*1.285*
11	*1.071*	*1.071*	*0.000*	*1.071*	*0.000*
12	*1.038*	*1.041*	*0.289*	*1.048*	*0.963*
13	*1.062*	*1.069*	*0.564*	*1.069*	*0.564*
14	*1.019*	*1.024*	*0.491*	*1.027*	*0.785*
15	*1.011*	*1.019*	*0.791*	*1.025*	*1.385*
16	*1.019*	*1.027*	*0.785*	*1.028*	*0.883*
17	*1.000*	*1.012*	*1.200*	*1.024*	*2.400*
18	*0.998*	*1.004*	*0.601*	*1.013*	*1.503*
19	*0.994*	*0.999*	*0.503*	*1.006*	*1.207*
20	*0.999*	*1.004*	*0.501*	*1.014*	*1.501*
21	*1.001*	*1.010*	*0.899*	*1.019*	*1.798*
22	*1.001*	*1.010*	*0.899*	*1.016*	*1.499*
23	*0.997*	*1.000*	*0.301*	*1.011*	*1.404*
24	*0.986*	*0.993*	*0.710*	*0.995*	*0.913*
25	*0.980*	*0.985*	*0.510*	*0.989*	*0.918*
26	*0.955*	*0.966*	*1.152*	*0.980*	*2.618*
27	*0.987*	*0.991*	*0.405*	*0.997*	*1.013*
28	*0.983*	*0.989*	*0.610*	*0.992*	*0.916*
29	*0.976*	*0.981*	*0.512*	*0.987*	*1.127*
30	*0.966*	*0.978*	*1.242*	*0.981*	*1.553*
Average % Increase		*0.705*		*1.414*	

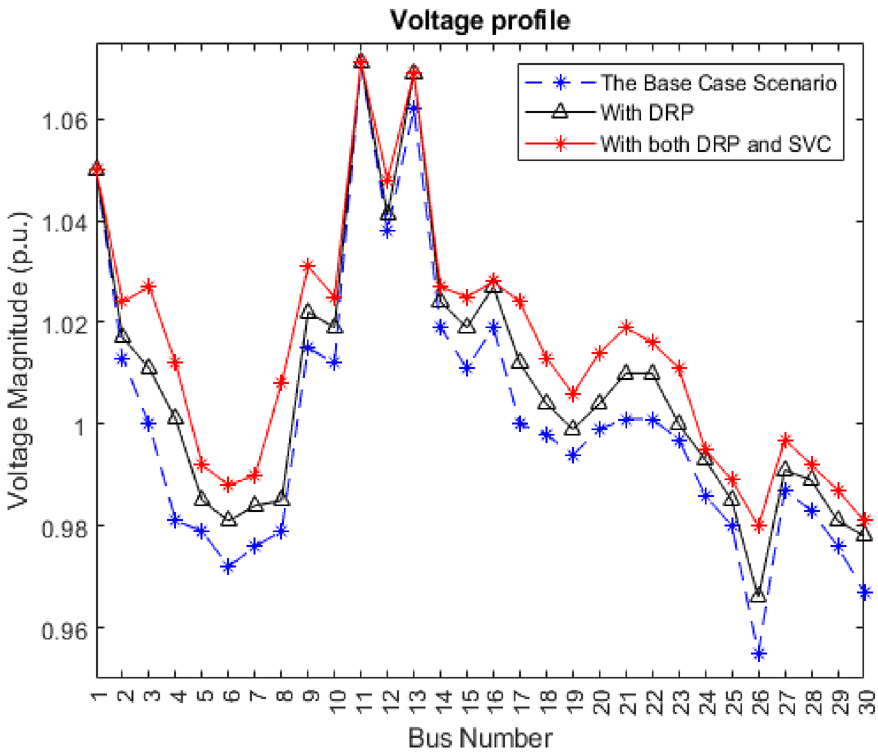

Fig.6. Voltage profiles for all the three Cases

<u>Discussions</u>

It can be seen from Table 3 and *Fig. 6* that:

i. There has been an average of 0.705% improvement in the bus voltage profile from Case 1 (the Base Case Scenario) where there was congestion, to Case 2 where the TOU program (DRP) was solely applied to relieve the congestion. The addition of the SVCs in Case 3 further improved the voltage profile of Case 2 by an average of 0.709%.

ii. The three voltage profiles show clearly that when there is congestion (Case 1), the bus voltage levels decrease, resulting in greater voltage deviations. This base case scenario does not only increase the system losses, but also creates voltage regulation problems for the customers.

iii. The application of TOU program (DRP) in Case 2 raised the bus voltages to very appreciable levels (average of 0.705% increase, and as a result, decreased the margin of deviation. However, when the SVCs were added to the DRP (Case 3), the bus voltage levels were further improved by 0.709% on the average, resulting in a total improvement of averagely 1.414% from Case 1.

iv. This really shows that even though DRPs single-handedly are effective in congestion management by enhancing system voltage profiles, adding SVC further enhances the system voltage profiles and thus reduces losses. Therefore, the combination of DRP and FACTS devices leads to better congestion management than DRPs only, by having a greater effect on system voltage profiles.

4.2 Effects on Generation Fuel Cost, Demand and System Losses

Figure 7 and Table 4 present a comparison of the total average demands, the total average fuel costs, and the total average losses for all the three cases.

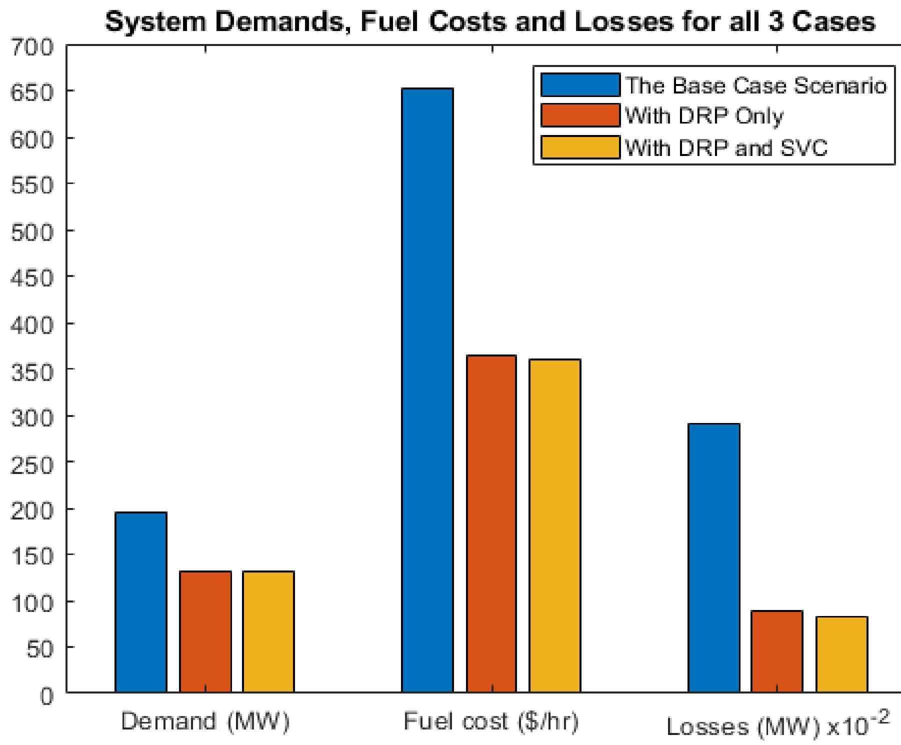

Fig. 7. Comparison of demands, fuel costs and losses for all the three cases

Table 4. Summary of results for the three (3) Cases in *Fig. 7*

Parameter	***Case 1 (Base case scenario)***	***Case 2 (With DRP only)***		***Case 3 (With both DRP and SVC)***	
			% Reduction		***% Reduction***
Demand (MW)	*195.6*	*132.50*	*32.25*	*132.50*	*32.25*
Generation Fuel Cost ($/hr)	*652.66*	*363.51*	*44.3*	*361.22*	*44.65*
System Losses (MW)	*2.91*	*0.89*	*69.42*	*0.84*	*71.13*

Discussions

The following analyses can be made from *Fig. 7* and Table 4:

On Fuel Cost:

i. The fuel cost in Case 1 is greater by 79.54% (652.66 \$/hr compared to 363.51 \$/hr) than that of Case 2, whilst that of Case 2 also being greater by 0.7% (363.52 \$/hr compared to 361 \$/hr) than that of Case 3. The high fuel cost in the Peak Period for Case 1 points to the fact that congestion presents some costs to both utilities and customers.

ii. However, with the application of the TOU program in Case 2, even though only 32% of the load responded to the TOU program, the fuel cost reduced drastically by 44.3% (as shown in *Fig.7*).

iii. The good results of Case 2 were slightly improved in Case 3, when both the DRP and the SVC were combined. As can be seen, the fuel cost further decreased slightly in Case 3. The fuel cost decreased from 363.51 \$/hr to 361.22 \$/hr, representing 0.63% (from 652.66 \$/hr in Case 1 to 361.22 \$/hr in Case 3, thus by 44.65% - compared with 44.3% for Case 2). This is attributed to the presence of the SVC.

On System Losses:

i. The system losses in Case 1 is greater by 226.97% (2.91 MW compared to 0.89 MW) than that of Case 2, whilst that of Case 2 also being greater by 5.95% (0.89 MW compared to 0.84 MW) than that of Case 3.

ii. Again, with the application of the TOU program in Case 2, with only 32% load participation in the TOU program, the losses reduced by 69.4%. The losses further reduced slightly in Case 3 by 5.62%, decreasing from 0.89 MW in Case 2 to 0.84 MW in Case 3.

On Demand:

i. Both the DRP only (Case 2) and the hybridized approach (Case 3) reduced the demand from 195.6 MW to 132.5 MW representing a reduction of 32.25%.

ii. The application of the SVC in Case 3 has no effect on the demand.

4.3 Effects on MVA flows on Congestion-Prone Lines

Figure 8 and Table 5 present results comparing the MVA flows in the congestion-prone lines for all the three cases.

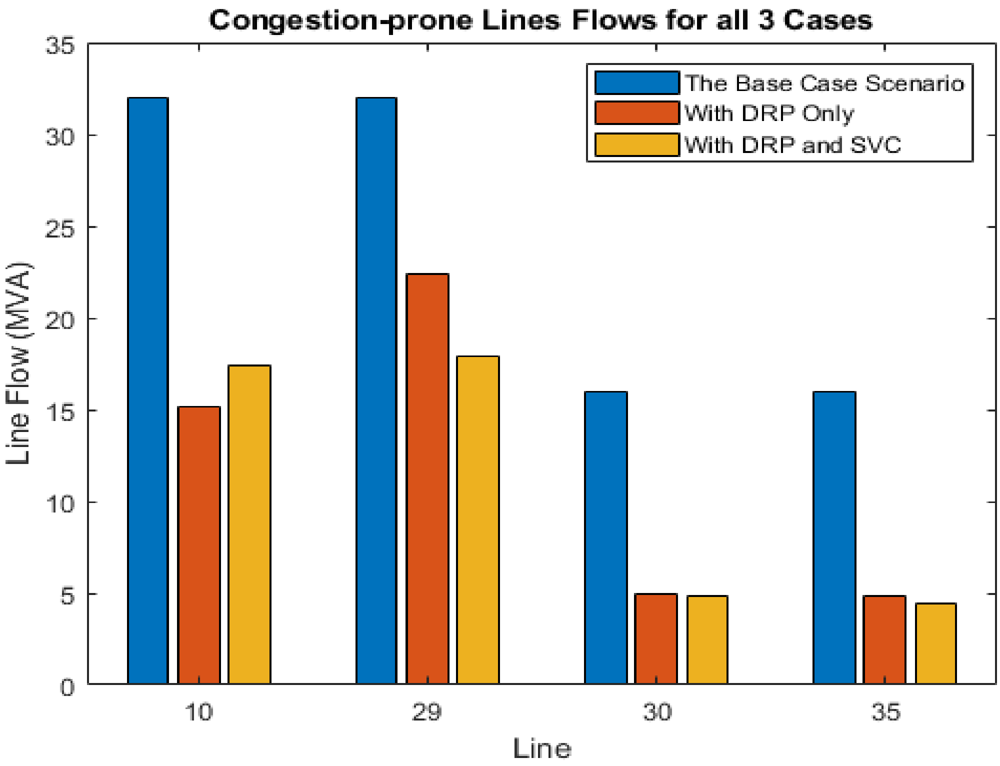

Fig.8. Comparison of MVA flows in congestion-prone lines for all three cases

Table 5. Comparison of MVA flows in congestion-prone lines for all three cases

Line	***MVA Flows (Limit)***	***MVA Flows (Case 1)***	***MVA Flows (Case 2)***	***MVA Flows (Case 3)***
10	*32.00*	*32.00*	*15.16*	*17.38*
29	*32.00*	*32.00*	*22.44*	*17.93*
30	*16.00*	*16.00*	*4.98*	*4.48*
35	*16.00*	*16.00*	*4.89*	*4.45*

<u>Discussions</u>

i. The flows (in MVA) in lines 10, 29, 30, and 35 are higher in the base case scenario (Case 1) than those in the same lines for Case 2 (DRP Only) and Case 3 (DRP and SVC). This is because, before the application of the TOU program, it can be seen in Table 5 that these lines were congested as the MVA flows in them reached their respective ratings. This means that the operating limits of these lines were reached.

ii. However, after the application of the TOU program (Case 2), it can clearly be seen from *Fig. 8* and Table 5 that the flows in these lines have reduced significantly, relieving the congestion in the lines.

iii. Case 3 also has the flows in lines 29, 30 and 35 being lower than the same lines for

Case 2. Again, these good results from the application of the TOU program (DRP) were further enhanced by the addition of the SVC, as can be seen in Case 3, where the flows in lines 29, 30 and 35 further reduced by 20.1% (from 22.44 MVA to 17.93 MVA), 10.04% (from 4.98 MVA to 4.48 MVA), and 9.0% (from 4.89 MVA to 4.45 MVA) respectively, compared to the flows in the same lines in Case 2.

8. CONCLUSION

In this paper, the effects of a combination of DRP and SVC FACTS device as a multi-objective approach for congestion management in transmission lines have been studied. The results show that, in comparison with the Base Case Scenario, the proposed method (employing both DR and SVC) reduced the Peak Period fuel cost from 652.66$/hr to 361.22$/hr, signifying a significant 44.65% reduction, as well as the losses in this same Peak Period from 2.913MW to 0.84MW, resulting in another significant 71.13% reduction. The voltage profile was also significantly enhanced by an average of 1.414% increase from the Base Case Scenario.

The high losses (2.913MW) and high generation fuel cost (652.66$/hr) in the Peak Period (represented by Case 1) again point to the fact that congestion presents some costs to both utilities and customers. Also, the proposed hybridized DRP-SVC method (represented by Case 3) further reduced VAR flows in the lines from 111.18MVAr in the Peak Period (Case 1) to 37.44MVAr, resulting in a significant 66.34% decrease in VAR flows (and hence losses), thus further decongesting the lines of reactive power and leading to an increased or higher line utilization factor (LUF) for the active power. The effectiveness of the proposed hybridized DR-SVC, multi-objective method in congestion management of transmission lines has thus been underscored.

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