# Optimal Placement of Biomass Distributed Generations with Intermittent Nature of Solar and Wind Renewable Sources

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**Abstract:- Today's energy market having flexibility for any time transaction of electricity for buyers and sellers due to open access. There are number of reason for occurrence of contingency in transmission network like generator failure, transmission line maintenance or transaction of electricity. This contingency we can mitigate by load shedding, generator rescheduling, or by using distributed generations. Optimal placement of DGs can be finding out by using Real Power Transmission Congestion Distribution factors. In this research work, Biomass Distributed Generations optimal placement is found out with the consideration of uncertainty of solar and winds DGs. As solar and wind generation is affected by geographical location. Uncertainty of wind and solar output is analyzed by Weibull probability distribution function and Beta probability distribution function respectively. By using Multi-objective Grey Wolf Optimization, optimal size of Biomass DGs found out to minimized Voltage stability Margin and Loss Margin can be minimized. Standard IEEE-30 bus system is used to validate performance of MO-GWO.**

***Keywords:-*** *MO-GWO, Distributed Generations, RPTCDFs, Contingency.*

## I. INTRODUCTION

The current state of traditional power generation cannot meet the rising demand for electricity on a global scale. Poor network design has left 16% of the world's population without access to electricity [11], and the control of transmission network congestion is a major issue. There are numerous factors that contribute to the congestion of electricity transmission lines, including generator failure, transmission line failure, and transformer maintenance. Since the customer has an open right to utilise power in this condition and the transmission line may exceed the permitted power, the situation is known as power transmission congestion. Congestion in a transmission network diminishes the line's capacity for power transfer, alters costs, and prevents the most effective supply from reaching distributors since it overloads the network to its maximum capacity. Congestion Management (CM) concerns involve actions that the independent system operator (ISO) must do to create a network that is congestion-free [1].

Energy consultants in the power industry and researchers in the literature introduce and use various CM strategies. Heuristic algorithms are first employed to reduce congestion. The impact of FACTS devices on the management of transmission line congestion is taken into consideration in [3] secure transactions for hybrid market model, as well as optimal rescheduling of generators with loadability constraints taken into account using secure transactions. In [4, it is shown how to formulate a multi-objective function that can account for daily active power loss and voltage deviation under a 24-hour load pattern, grouping residential, industrial, and commercial loads utilising repeating backward-forward sweep-based load flow, and modelling PEV load The particle swarm optimization (PSO) technique is used to deploy distributed generation (DG) within the primary distribution system in order to [5] reduce the overall loss of power. In order to reduce power loss, [6] introduced a population-based method called particle swarm optimization (PSO) for optimal planning of the position and sizing of various types of DG units in the distribution network. Bidding technique is another another modelling tool utilised in congestion management. In [7], a two-level optimization problem employing bacterial foraging optimization is framed, with suppliers' competitors bidding nature and its effect on congestion, whereas in [8,] bidding strategy is based on evolutionary bipartite complex network theory. [9] suggested post-congestion system security and dynamic voltage stability for congestion control.

The hybrid Harmony Search Algorithm technique is used in [10] to minimise power losses in radial distribution networks and provides an improvement in bus voltage profile by selecting ideal locations, optimally sized distributed generators, and shunt capacitors. The topic of locating and sizing distributed generation units from renewable energy sources was evaluated in [11] using state-of-the-art methods.

Many research studies have used DGs in primary and secondary distribution systems, but there is actual little evidence of their use in transmission networks. To extract

ISSN No:-2456-2165

technical and economic benefits from the systems, higher ratings (from 1 MW to a few MWs) of DGs are linked to huge power networks, while minor ratings (from a few KWs to 1 MW) are coupled to distribution systems [12]. In [13], a Multi-Line CM (MLCM) problem is resolved by a hybrid Nelder-Mead – Fuzzy Adaptive Particle Swarm Optimization (HNM-FAPSO). The sensitivity of crowded lines to bus injections is used to suggest an efficient congestion management algorithm in a multilateral trading model given in [14]. A new method of Ant Lion Optimization (ALO) algorithm-based congestion management is introduced in [15] by rearranging the real power output of the participating generators. A comparison of viable transactions between power utilities in a bilateral and multilateral setting, with the financial benefits of the power companies taken into account according to the deregulated power market's norms is studied in [16]. Embedded transmission cost allocation mechanisms, such as Postage Stamp and Contract Path, are applied in [17] for the first time. Second, flow mile technologies such as the MW-MILE and MVA-MILE are employed. Finally, flow cost approaches such as MW-COST and MVA-COST are proposed and developed.

A strategy for arranging different kinds of renewable distributed generation (DG) units in the distribution system to diminish yearly energy loss has been developed in [18] this approach is focused on developing a probabilistic generation-load model that takes into account all potential operating scenarios for renewable DG units and their probability. In [19] With the load coming from renewable, battery storage, or both, wind farms and solar parks with the same or various types of wind turbines and PV modules are explored. In [20] examine the effects of various DGs operational modes on system routine when system reconfiguration, DG generation, and tap changer settings are all set to their optimal values at the same time. The major goal of the ideal setup procedure is to reduce day-to-day power losses as much as possible. Until date, DG capacities have been determined based on either economic or practical factors, both of which point to the system's impaired technical performance or financial load [21]. Similarly, whereas linking renewable energy DGs to the current system, several studies failed to address appropriate capabilities and probabilistic nature [22].

As a result, an attempt was made to get DG sizes in order to increase the performance of the considered system utilizing MOO, which stays a significant addition towards the current CM problem. Likewise, the alternating nature of renewable energy DGs such as PV and wind has been modelled with PDFs and is used to mix with the present system. Furthermore, the controllable output of Biomass DG is evaluated using a multi-objective optimization background then resolved using MO-GWO.

The remainder of the paper is ordered as follows: The probabilistic model of the investigated renewable energy DGs is shown in section II. Section III displays the multi-objective problem invention for CM the formulae for optimal DG positioning are shown in Section IV, Section V shows the Multi Objective Grey wolf optimization algorithm aimed at resolving the multi-objective function. The case study and conclusions are covered in Sections VI and VII, respectively.

## II. PROBABILISTIC PRODUCTION MODEL OF RENEWABLE SOURCES.

The solar and wind generation is totally depends upon the geographical area. So outputs of these renewable sources are intermittent. Whereas biomass generation output is constant in nature which will be controlled as per requirement only. For optimal output of solar array and wind turbine, there is need to analyzed characteristic of solar irradiations and wind speed. So need of selection probability distribution factor (PDF) which gives accurate results. Beta and Weibull PDF are generally intended for modeling of renewable sources. Solar PV modeling and wind speed modeling is done from [23]. The constant PDF has been divided into states (periods) where the sun irradiance and wind speed are contained within predetermined ranges. Solar array and Wind Turbine power generation is determined by the likelihood of all conceivable states for that hour.

### *A. Solar Power Generation Model*

Solar irradiance is thought to be probabilistic, according to Beta PDF [23]. “The solar irradiance Ṣt (kW/m2) beta distribution over time segment’t’ is given by”,

$$f_b^t(ṣ) = \frac{\Gamma(\alpha^t + \beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} * (ṣ^t)^{(\alpha^t-1)} * (1 - ṣ^t)^{(\beta^t-1)} \quad (1)$$
$$for\ 0 \le ṣ^t \le 1, \qquad \alpha^t \ge 0, \beta^t \ge 0$$

Where,

$ṣ^t$ = solar irradiance KW/m2;

$\mathrm{f}_\mathrm{b}^\mathrm{t}(ṣ)$ = Beta distribution functions of $s$;

α, β = parameters of the Beta distribution function i.e shape parameters at ‘t’ time segment;

Γ = Gamma function;

The mean (μ) and standard deviation (σ) of irradiance for the corresponding time segment can be used to derive Beta PDF shape parameters β and α.

$$\beta = (1 - \mu) * \left[\frac{\mu * (1 + \mu)}{\sigma^2} - 1\right] \quad (2)$$

$$\alpha = \frac{\mu * \beta}{1 - \mu} \quad (3)$$

The hourly average output power of a Solar can be determined as follows for a certain time segment 't' :

$$P^t{}_{PV} = \sum_{g=1}^{N_{ṣ}} PG_{PVg} * P_{ṣ}\left(ṣ^t{}_g\right) \qquad (4)$$

Where,
$g$: Singinifies the state variable
$N_{ṣ}$: is the number of discrete solar irradiance state
$Ṣ^t{}_g$: is the gth level/state of solar irradiance at tth time segment.

The PV array's output power is determined by the site's ambient temperature and irradiance. The following equation depicts PV array power generation as a function of solar irradiation at the gth state:

$$PG_{PVg}(sav) = N_{pvmod} * FF * V_g * I_g \qquad (5)$$

Where,
$N_{pvmod}$ = total number of PV modules used to create a PV array.

The current-voltage characteristics of a PV module can be derived using the following relationships for a given radiation level and ambient temperature TA (0C).

$$I_g = Sav\left[I_{sc} + K_I\left(T_{cg} - 25\right)\right] \qquad (6)$$

$$V_g = \left[V_{oc} - K_V * \left(T_{cg}\right)\right] \qquad (7)$$

$$T_{cg} = T_A + Sag\left(\frac{N_{OT} - 20}{0.8}\right) \qquad (8)$$

$$FF = \frac{V_{MPP} * I_{MPP}}{V_{OC} * I_{SC}} \qquad (9)$$

Where,
$T_{cg}$ : is cell temperature at gth state (ºC)
$T_A$ : Ambient Temperature (ºC)
$K_{I,}K_V$ : are current and voltage temperature co-efficient (A/ ºC and V/ ºC)
$N_{OT}$: is the nominal operating temperature of cell (ºC)
$FF$: is the fill factor
$V_{OC}$ and $I_{SC}$ : are open circuit voltage (V) and short circuit current (A)
$V_{MPP}$ and $I_{MPP}$ : are Voltage (V) and current (A) at maximum power point respectively.
$Sav$: mean value of solar irradiance.

The solar irradiation probability for each state over any given time period is computed as:

$$P_{ṣ}\left(Ṣ^t{}_g\right) = \begin{cases} \displaystyle\int_0^{\left(ṣ^t{}_g + ṣ^t{}_{g+1}\right)/2} f^t{}_{ṣ}(Ṣ)ds & for\ g = 1 \\ \displaystyle\int_{\left(ṣ^t{}_{g-1} + ṣ^t{}_g\right)/2}^{\left(ṣ^t{}_g + ṣ^t{}_{g+1}\right)/2} f^t{}_{ṣ}(Ṣ)ds & for\ g = 2 \ldots\ldots (N_s - 1) \\ \displaystyle\int_{\left(ṣ^t{}_{g-1} + ṣṣ^t{}_g\right)/2}^{\infty} f^t{}_{ṣ}(Ṣ)ds & for\ g = N_s \end{cases} \qquad (10)$$

*B. Wind power generation model*

Weibull PDF was chosen to explain stochastic behavior of wind speed over a predetermined time period. For the wind speed at the tth time segment, the Weibull distribution can be written as:

ISSN No:-2456-2165

$$f\omega(\mathrm{v}) = \frac{\mathrm{k}}{\mathrm{c}} * \frac{\mathrm{v}^{\mathrm{k}-1}}{\mathrm{c}} * exp\left[-\left(\frac{\mathrm{v}}{\mathrm{c}}\right)^{\mathrm{k}}\right] \tag{11}$$

Where is c referred to as the scale index, and k is known as the shape index. which is calculate by following equation.

$$\mathrm{k} = \left(\frac{\sigma^{-1.086}}{\mu^{-1.086}}\right) \tag{12}$$

$$\mathrm{c} = \frac{\mu_v}{\Gamma(1 + 1/\mathrm{k})} \tag{13}$$

$\mu_v$ and $\sigma$ are mean and standard deviation of wind speed at time segment.

The power output per hour from WT $(P^t WT)$ with respect to tth time segment is expressed as [2]:

$$(P^t WT) = \sum_{g=1}^{N_v} \mathrm{PG}_{\mathrm{WTg}} * \mathrm{P_v}\left(\mathrm{v^t}_{\mathrm{g}}\right) \tag{14}$$

The following formula is used to determine the likelihood of wind speed for each state during any given time period:

$$P_v(\mathrm{v}^t g) = \begin{cases} \int_{0}^{\frac{(\mathrm{v}^t{}_g + \mathrm{v}^t{}_{g+1})}{2}} f_v^t\,(\mathrm{v})d\mathrm{v} & for\ g = 1 \\ \int_{\frac{(\mathrm{v}^t{}_{g-1} + \mathrm{v}^t{}_g)}{2}}^{\frac{(\mathrm{v}^t{}_g + \mathrm{v}^t{}_{g+1})}{2}} f_v^t\,(\mathrm{v})d\mathrm{v} & for\ g = 2 \dots \dots (N_v - 1) \\ \int_{\frac{(\mathrm{v}^t{}_{g-1} + \mathrm{v}^t{}_g)}{2}}^{\infty} f_v^t(\mathrm{v})d\mathrm{v} & for\ g = (N_v) \end{cases} \tag{15}$$

Power output from WT at a speed $(\mathrm{v}_{ag})$ for state 'g' is:

$$\begin{cases} 0 & \mathrm{v}_{ag} < \mathrm{v}_{cin}\ \ or\ \ \mathrm{v}_{ag} > \mathrm{v}_{cout} \\ (a * \mathrm{v}^3{}_{ag} + b * P_{rated}) & \mathrm{v}_{cin} \le \mathrm{v}_{ag} \le or\ \mathrm{v}_N \\ P_{rated} & \mathrm{v}_N \le \mathrm{v}_{ag} \le \mathrm{v}_{count} \end{cases} \tag{16}$$

"where $P_{rated}$ is the highest power that WT can produce; $\mathrm{v}_{cout}$ is the cut-out wind speed; Constants $a$ and $b$ are function of cut-in wind speed ($\mathrm{v}_{cin}$) and nominal wind speed ($\mathrm{v}_N$), and obtained as" [2]:

$$a = \frac{P_{rated}}{(\mathrm{v}^3{}_N - \mathrm{v}^3{}_{cin})} \tag{17}$$

$$b = \frac{\mathrm{v}^3{}_{cin}}{(\mathrm{v}^3{}_N - \mathrm{v}^3{}_{cin})} \tag{18}$$

ISSN No:-2456-2165

## III. CONGESTION PROBLEM

Bilateral and multilateral dealings are of special relevance in a deregulated environment because generators and customers interested in straight contracts or through power agents. They decide on the amount of power and the charge of electricity. The bilateral transaction can be represented as follows:

$$P^i{}_g - P^j{}_d = 0 \tag{19}$$

Where, $P^i{}_g$ = the power generation from bus i
$P^j{}_d$ = the contracted power demand at bus j.

The market is cleared in double-sided bidding by exploiting social welfare (SW) within physical restrictions, and then the independent System Operator (ISO) assesses the power system's security. Congestion Management (CM) is used in the event of system insecurity, and some generators may be asked to change their output. As a result, in the event of congestion, the generators may make more profit or lose more money. To avoid this, it is preferable to incorporate ideal DG sizes at appropriate load pockets as an option to relieve overcrowding. The sizes of the Distributed Generations (DGs) are calculated using a multi-objective problem with the primary objectives of CGC, VSM, and LM.

### *A. Conventional Generation Cost (CGC)*

$$\text{Min CGC} = \sum_{i=1}^{N_g} \left(\frac{1}{2} \mathrm{a_{g,i}} * \mathrm{p^2{}_{g,i}} + \mathrm{b_{g,i}} * \mathrm{p_{g,i}} + \mathrm{c_{g,i}}\right) \tag{20}$$

Here, $a_{g,i}, b_{g,i}, c_{g,i}$ are the cost coefficients, $P_{gi}$ is the real power output of the $i^{th}$ conventional generators, $N_g$ is the total number of conventional generators.

➢ *The Limitations of this Objective Function are,*

- Generator constraints: The following inequality constraints are used to describe the lower and higher generation limits that are applied to each generator output during the design phase.

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \tag{21}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \tag{22}$$

Where, $P_g^{min}$ and $P_g^{max}$ are the minimum and maximum real power production's of each generator and $Q_g^{min}$ and $Q_g^{max}$ are each generator's reactive power production's minimum and maximum values.

- Bus voltage constraints: When solving OPF, the lower and upper bus voltage limitations must be properly validated since the bus voltage stated in per unit has a considerable impact on the stability aspect.

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{23}$$

$$\delta_i{}^{min} \leq \delta_i \leq \delta_i{}^{max} \tag{24}$$

Where $V^{min}$ and $V^{max}$ are the bus's permitted minimum and maximum voltages. Typically, this is understood to be 0.95 and 1.05 per unit, respectively. $\delta_i$, $\delta_i{}^{min}$, $\delta_i{}^{max}$ are the voltage angle of bus i and j its minimum and maximum limits respectively.

- Power balance constraints: According to the equilibrium principle, the whole system generation must match the total system load, which is expressed as an equality constraint as follows:

$$P_{gi} - P_{di} = |V_i| \sum_{j=1}^{nbus} \left\{ \left(G_{ij} cos\delta_{ij} + B_{ij} sin\delta_{ij}\right) |V_j| \right\} \tag{25}$$

ISSN No:-2456-2165

$$Q_{gi} - Q_{di} = + \left|V_i\right| \sum_{j=1}^{nbus} \left(-B_{ij} cos_{\delta ij} + G_{ij} sin_{\delta ij}\right) \left|V_j\right| \qquad (26)$$

Where Gij and Bij are the conductance and susceptance of line i-j respectively, Pgi and Pdi are the active power generation and demand at bus i respectively, Qgi and Qdi are the reactive power generation and demand at bus i respectively. $\delta_{ij} = \delta_j - \delta_i$

- Transmission line MVA constraints: The MVA ratings of the transmission lines are restricted depending on the conductors used, and the line flow in a transmission line should be within its MVA limit, which is the primary determinant of the occurrence of congestion.

$$S_l \leq S_l^{max} \qquad (27)$$

Where, $S_l^{max}$ is the extreme tolerable MVA line flow in line l.

*B. Voltage Stability Margin (VSM)*

Here, the voltage variations from the established limits for before DGs case and after DGs case are diminished. The following is an expression for the objective function:

Minimize VSM

$$= \frac{\sum_{i=2}^{N_{bus}} \left(V_i^{DG} - 1.0\right)^2}{\sum_{i=2}^{N_{bus}} \left(V_i^{0} - 1.0\right)^2} \qquad (28)$$

Where, $V_i^0$, $V_i^{DG}$ are the Voltage at bus $i$ before and after connecting the DG respectively.

*C. Loss Margin (LM)*

The first objective is to minimize the real power losses after the injection of DG into the transmission system. This objective can be stated as follows:

Minimize LM

$$= \frac{P_{Loss}^{DG}}{P_{Loss}^{0}} \qquad (29)$$

Here, $P_{Loss}^0$, $P_{Loss}^{DG}$ are the real power losses before and after connecting DG respectively.

The fitness function comprising of multiple objectives is shown as below:

$$Minimize\ F = W1 * CGC + W2 * VSM + W3 * LM \qquad (30)$$

The above fitness function is subjected to the constraints specified in above equations along with constraint specified as below.

$$\sum_{n=1}^{T} W_n = 1 \qquad (31)$$

Where, Wn is the nth Weight factor and $T$ is the total number of objectives.

The second approach involves explicitly invoking for the complete collection of Pareto optima in order to solve the MOO. Once a collection of alternatives has been found, the best compromise is found based on the situation. In this work, we utilized the fuzzy set theory to select the best compromise solution. In this method, the corresponding membership function value to each objective function is figured out using the below equation:

ISSN No:-2456-2165

$$\sigma_i = \begin{cases} 1 & if\ F_i \le F_i^{min} \\ \dfrac{F_i^{min} - F_i}{F_i - F_i^{max}} & if\ F_i^{min} \le F_i \le F_i^{max} \\ 0 & if\ F_i \le F_i^{max} \end{cases}$$

Here $F_i^{\max}$ and $F_i^{\min}$ are the maximum and minimum values of the $i^{th}$ objective function obtained in Pareto set. The normalized value of the membership function is calculated as follows:

$$\sigma^N = \frac{\sum_{i=1}^{T} \sigma_i^N}{\sum_{j=1}^{m} \sum_{i=1}^{T} \sigma_i^N} \quad (32)$$

Where 'm' is the number of solutions that are not dominated. The compromise $\sigma^N$ that offers the most value is the best.

## IV. OPTIMAL ALLOCATION OF DGS

To alleviate congestion, a ZBUS-based contribution factors [22] grounded technique is planned for putting the DG. Likewise, the PTCDFs planned in [24] are used to determine the best location of DGs. It's the ratio of the variation in actual power flow (Pij) through a transmission line connecting buses i and j to the variation in power insertion (Pn) on a specific bus n. The following is a mathematical illustration of PTCDFs for line k:

$$PTCDF_n^K = \frac{\Delta P_{ij}}{\Delta P_n} \quad (33)$$

The real power flow in a line-k connected between bus-i and bus-j can be written as:

$$P_{ij} = V_i V_j Y_{ij} cos(\theta_{ij} + \delta_j - \delta_i) - V_i^2 Y_{ij} cos\theta_{ij} \quad (34)$$

Vi and δi stand for the voltage strength and angle at bus i respectively. Yij and θij are the ijth element of the Ybus matrix's magnitude and angle, respectively.

Equ. (a) can be represented as follows using Taylor series approximation:

$$\Delta P_{ij} = \frac{\partial P_{ij}}{\partial \delta_i} \Delta \delta_i + \frac{\partial P_{ij}}{\partial \delta_j} \Delta \delta_j + \frac{\partial P_{ij}}{\partial V_i} \Delta V_i + \frac{\partial P_{ij}}{\partial V_j} \Delta V_j \quad (35)$$

Equation (b) can be written as:

$$\Delta P_{ij} = \alpha_{ij} \Delta_{\delta i} + b_{ij} \Delta \delta_j + c_{ij} \Delta V_i + d_{ij} \Delta V_j \quad (36)$$

With respect to the variables δ and V, the partial derivatives of real power flow (34) can be used to get the coefficients appearing in (36) as;

$$\alpha_{ij} = V_i V_j Y_{ij} sin(\theta_{ij} + \delta_j - \delta_i) \quad (37)$$

$$b_{ij} = -V_i V_j Y_{ij} sin(\theta_{ij} + \delta_j - \delta_i) \quad (38)$$

$$c_{ij} = V_j Y_{ij} cos(\theta_{ij} + \delta_j - \delta_i) - 2 V_i Y_{ij} cos\theta_{ij} \quad (39)$$

$$d_{ij} = V_i Y_{ij} cos(\theta_{ij} + \delta_j - \delta_i) \quad (40)$$

For determination of PTCDFs, the following Jacobin relationship has been used:

$$\Delta P = J_{11} \Delta \delta + J_{12} \Delta V \quad (41)$$

By ignoring P-V coupling, (41) rewritten as per follows,

$$\Delta P = J_{11} \Delta \delta \quad (42)$$

From (42) , we get

$$\Delta\delta = [J_{11}]^{-1}[\Delta P] = [M][\Delta P] \quad (43)$$

So from above equation,

$$\Delta\delta_i = \sum_{l=1}^{n} m_{il}\, \Delta P_l$$

$$i = 1,2, \dots n, i \neq s \quad (44)$$

Since it is believed that the effect of a change in bus voltage on actual power flow is minimal, Equation (36) can be rewritten as follows:

$$\Delta P_{ij} = \alpha_{ij}\Delta\delta_i + b_{ij}\Delta\delta_j \quad (45)$$

Substituting (44) into (45) we get

$$\Delta P_{ij} = \alpha_{ij} \sum_{l=1}^{n} m_{il}\, \Delta P_l + b_{ij} \sum_{l=1}^{n} m_{jl}\, \Delta P_l \quad (46)$$

Or

$$\Delta P_{ij} = (\alpha_{ij} m_{i1} + b_{ij} m_{j1})\Delta P_1 + (\alpha_{ij} m_{j2} + b_{ij} m_{j2})\Delta P_2 + \dots\dots\dots + (\alpha_{ij} m_{in} + b_{ij} m_{jn})\Delta P_n \quad (47)$$

Equation (47) can be written as,

$$\Delta P_{ij} = PTCDF_2^K \Delta P_1 + PTCDF_2^K \Delta P_2 + PTCDF_n^k \Delta P_n \quad (48)$$

Where,

$$PTCDF_2^K = \alpha_{ij} m_{i1} + b_{ij} m_{j1} \quad (49)$$

Are actual distribution variables for transmission congestion that correspond to bus n and the line k that connects bus I and bus j. In the current study, every change in the system operating condition will cause the Jacobian used to calculate the PTCDFs to change. The suggested approach, however, is quick and can be used to update the PTCDFs. The acquired values are then organized in descending order to determine the buses to be installed in what order.

## V. MULTI – OBJECTIVE GREY WOLF OPTIMIZATION (MO-GWO)

The optimal capacity of DG is determined in this work by diminishing the solo objective function by means of the MO-GWO method. Mirjalili originally introduced Grey Wolf Optimizer in the year 2014 [25]. The algorithm is constructed on the food-gathering policy of Grey wolves. Grey wolves usually travel in packs of five to twelve wolves. The wolves surround the target in the progression of chasing. The mathematical model of the encirclement performance is displayed below:

$$\vec{D} = \left| \vec{C}.\overrightarrow{X_p}(k) - \vec{X}(k) \right| \quad (50)$$

$$\vec{X}(k+1) = \overrightarrow{X_p}(k) - \vec{A}.\vec{D} \quad (51)$$

Here, $\vec{C} = 2 * \overrightarrow{r3}$ and $\vec{A} = 2 * \vec{r} * \overrightarrow{r4} - \vec{r}$

Where, $\vec{A}, \vec{C}$ = coefficient vectors,

$\vec{X}_P(k), \vec{X}(k)$ = position vectors of target also wolf in the $k^{th}$ iteration.

$\vec{r}_3$ , $\vec{r}_4$ = arbitrary paths preferred among [0, 1],

$\vec{r}$ = linear variation amongst [0, 2] for each repetition count.

As they develop more experience in choosing the best options, wolves take the lead in this hunting process. The first three best solutions are more knowledgeable about prospective solutions; therefore we save them and require the remaining search agents keep informed their locations in accordance with the top search agent's position. The following is a formula for adjusting the positions of agents:

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_\alpha} * \overrightarrow{X_\alpha}(k) - \vec{X}(k)\right| \quad (52)$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_\beta} * \overrightarrow{X_\beta}(k) - \vec{X}(k)\right| \quad (53)$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_\delta} * \overrightarrow{X_\delta}(k) - \vec{X}(k)\right| \quad (54)$$

$$\overrightarrow{X_1}(k+1) = \overrightarrow{X_\alpha}(k) - \overrightarrow{A_\alpha}.\overrightarrow{D_\alpha} \quad (55)$$

$$\overrightarrow{X_2}(k+1) = \overrightarrow{X_\beta}(k) - \overrightarrow{A_\beta}.\overrightarrow{D_\beta} \quad (56)$$

$$\overrightarrow{X_3}(k+1) = \overrightarrow{X_\delta}(k) - \overrightarrow{A_\delta}.\overrightarrow{D_\delta} \quad (57)$$

$$\vec{X}(k+1) = \frac{\overrightarrow{X_\alpha}(k+1) + \overrightarrow{X_\beta}(k+1) + \overrightarrow{X_\delta}(k+1)}{3} \quad (58)$$

## VI. CASE STUDY AND RESULTS

Here, insertion of Biomass DGs has done with the consideration of intermittent nature of solar and wind DGs in transmission grid to mitigate congestion of grid. Different sizes of biomass DGs are calculated by using MO-GWO.

### *A. Resource Evaluation*

Because to its proximity to the Bay of Bengal and the Tropic of Cancer, the Kakdwip region has different periodic fluctuations in climate. Summer, Autumn, Winter, and Spring are the four seasons studied during a year. There are 24 segments per season, each of which refers to a specific hourly intermission throughout the season. As a result, the year is divided into 96-time pieces (24 for each season) [23].

Figure 1 shows output of solar and wind DGs the output of solar and wind DGs which is obtained by considering previous data collected at the site, calculate the mean and standard deviation of solar irradiance and wind speed. Then, for each hour, a Beta and Weibull PDF is generated.

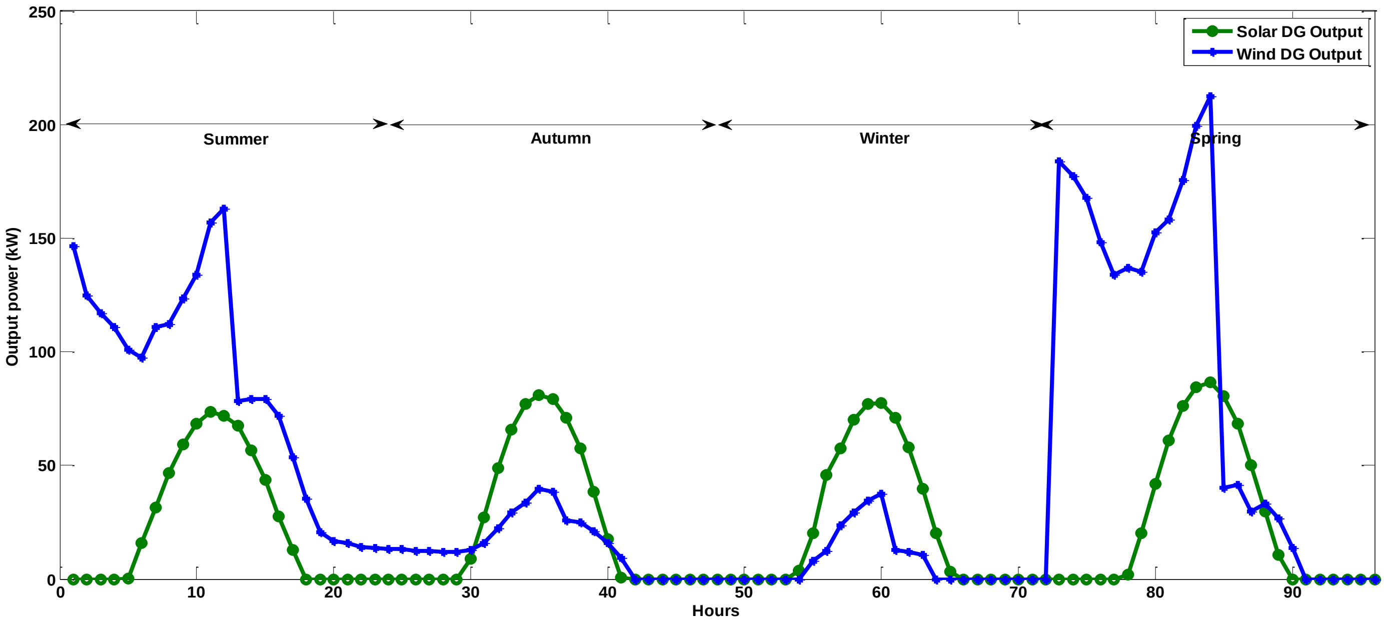


Fig 1 PV and WT DG Outputs for Arbitrarily Selected Location

*B. Contingency Creation*

The effectiveness of the proposed MOO-based CM techniques is investigated in this study using a conventional IEEE 30 bus system. The simulations were done on a personal computer with 4 GB RAM and a 2.30 GHz processor, and the proposed methodologies were implemented in MATLAB. For the IEEE 30 test bus system, the population count is set to 20. For the test bus system, the total iterations are also set to 100. Fig. 2 shows single line diagram of IEEE 30 bus.

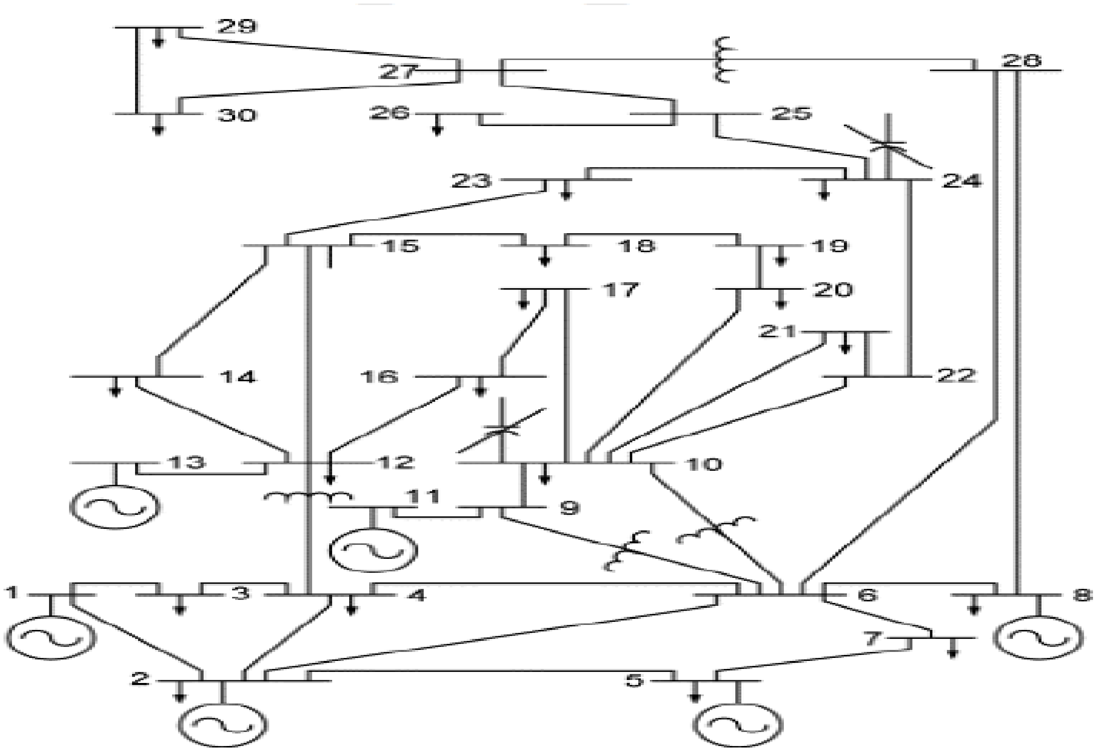


Fig 2 Line Diag. of IEEE 30 Bus

The test system establishes the deregulation scenario through bilateral and multilateral dealings. Transaction details are taken from [1]. The power flow in two transmission lines has surpassed their maximum MVA limit after these transactions were added to the optimal timetable. The apparent power flow in line 10, which connects buses 6 and 8, is 36.15 MVA, compared to its MVA limit of 32 MVA.

In the simplest scenario, there is no system congestion; we performed the basic OPF to evaluate the generations, line flows and total losses. The results are obtained by GWO as well as PSO to validate. To acquire the active powers of the generators, basic OPF is conducted using fuel cost function as the objective, the net Slij of the transmission corridors, and the total loss in the system. With bus 1 serving as the reference bus, the active power outputs of all other generators—aside from bus 1—are taken into account as the variables for the basic Optimal Power Flow (OPF) run. The outcomes of OPF's run are shown in table 1 as results. When compared to the PSO technique, the production cost obtained by adopting the GWO is 801.8441 ($/h), which is the same.

Table 1 Results of Basic Case Load Flow

| Generator Number | PSO | GWO |
|---|---|---|
| $G_1$ | 176.6624 | 176.6482 |
| $G_2$ | 48.8103 | 48.7265 |
| $G_3$ | 21.4607 | 21.5016 |
| $G_4$ | 21.7339 | 21.7097 |
| $G_5$ | 12.1028 | 12.1788 |
| $G_6$ | 12.0 | 12.0 |
| $F$ ($/h) | 801.8437 | 801.8441 |
| $P_{Loss}^{0}$ (MW) | 9.3507 | 9.3648 |
| $S_{6-8}$ (MVA) | 35.14 | 36.15 |
| $S_{6-8}^{Limit}$ | 32 | 32 |
| $S_{6-8}$ (MVA) | --- | 25.19 |

PTCDFs are used to assess the best places to place the ideal-sized DGs given the congested line 6–8, figure 3 shows graphical representation of PTCDF for each bus.

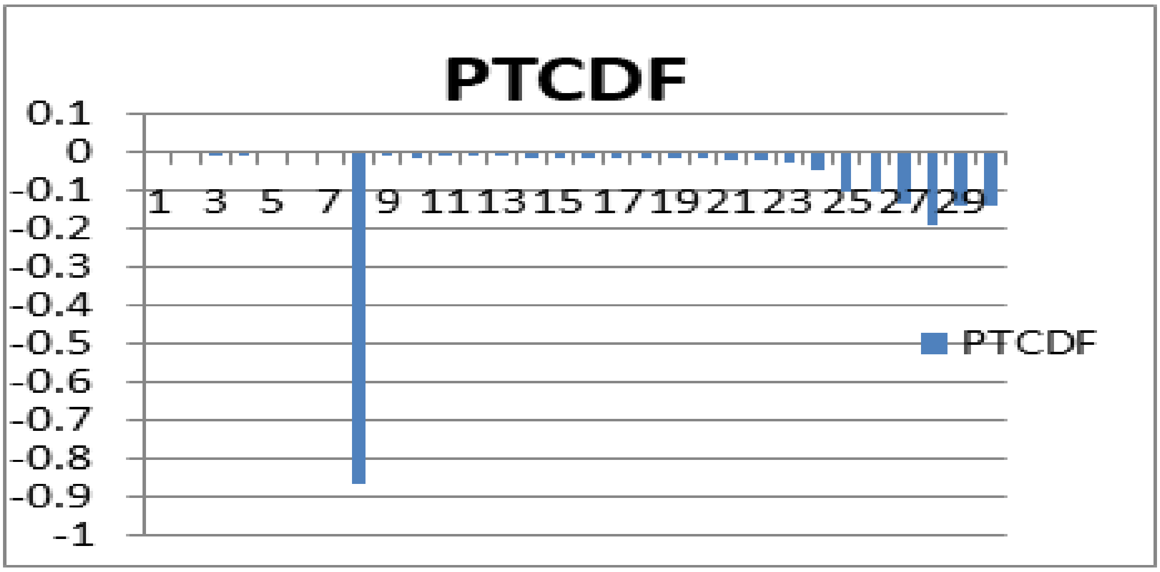


Fig 3 Graph of Value of PTCDF for Each Bus

So, to mitigate the congestion in the line 6 – 8, it is decided to incorporate WT and Solar DGs at buses 28 and 29 and Biomass DG at bus 8. The capacity of Biomass DG has been found by optimizing the proposed objective function with GWO algorithm. It is first optimized for a single objective, and then a multi-objective approach is used to resolve it.

*C. Results with Single Objective*

Here weight factor is consider is 0.25,0.25 and 0.5 for W1, W2, W3 respectively throughout run of algorithm program. BM-DG capacity and real losses is calculated when following single objective is considered.

I] Voltage Deviation as a single objective. II] Minimization of Losses as a single objective.

Minimum and maximum BMDG capacity and losses for four seasons throughout year is obtained with consideration of this single objective gives in table 2,3 and 4,5 respectively.

Table 2 BMDG Capacities when Voltage Deviation Consideration

| | **Summer** | **Autumn** | **Winter** | **Spring** |
|---|---|---|---|---|
| Minimum | 8.5544 | 8.482 | 8.5169 | 8.4787 |
| Maximum | 9.2846 | 9.2848 | 9.2627 | 9.1666 |
| Mean | 8.8931 | 9.0057 | 8.8983 | 8.8683 |
| Std Deviation | 0.24376 | 0.290126 | 0.244942 | 0.247459 |

Table 3 BMDG Capacities when Minimization of Losses Consideration

| | **Summer** | **Autumn** | **Winter** | **Spring** |
|---|---|---|---|---|
| Minimum | 58.7156 | 58.6481 | 58.6505 | 58.6432 |
| Maximum | 59.2902 | 59.3174 | 59.1984 | 59.2941 |
| Mean | 58.9325 | 58.9481 | 58.9537 | 58.9707 |
| Std Deviation | 0.20908345 | 0.190095 | 0.195939 | 0.21176 |

Table 4 Real Power when Voltage Deviation Consideration

| | **Summer** | **Autumn** | **Winter** | **Spring** |
|---|---|---|---|---|
| Minimum | 9.5814 | 9.5968 | 9.5886 | 9.7127 |
| Maximum | 10.2181 | 10.2232 | 10.1951 | 10.2226 |
| Mean | 9.9032 | 9.8713 | 9.8396 | 10.0029 |
| Std Deviation | 0.20174 | 0.168804 | 0.207173 | 0.178986 |

Table 5 Real Power when Loss Minimization Objective Consideration

| | Summer | Autumn | Winter | Spring |
|---|---|---|---|---|
| Minimum | 6.977 | 6.9779 | 6.9763 | 6.9818 |
| Maximum | 7.0217 | 7.0205 | 7.0233 | 7.0237 |
| Mean | 6.9962 | 6.9989 | 7.0019 | 7.0031 |
| Std Deviation | 0.014368 | 0.0125 | 0.014376 | 0.015646 |

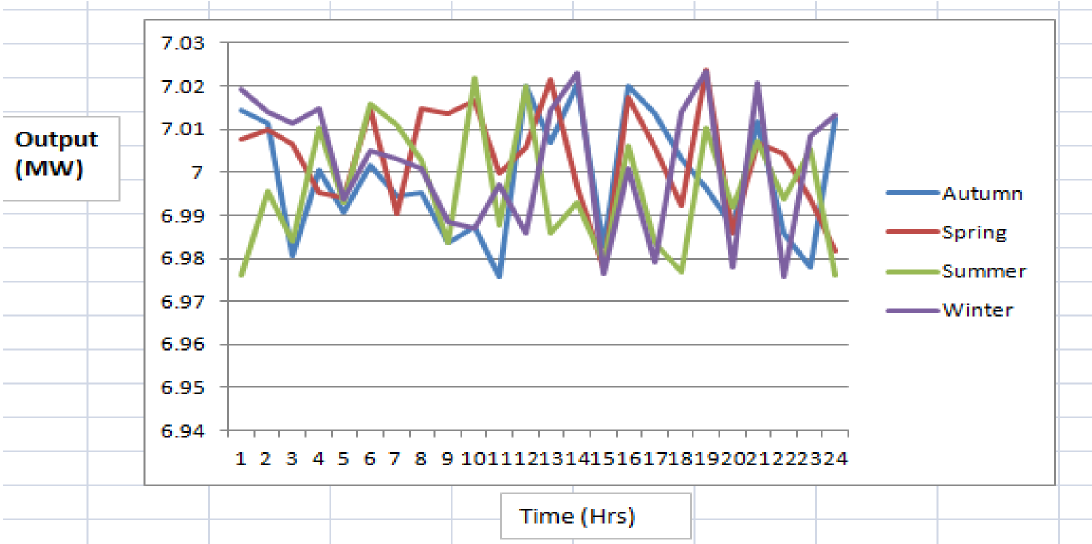


Fig 4 Losses with DGs when Consideration of Losses as a Objectives.

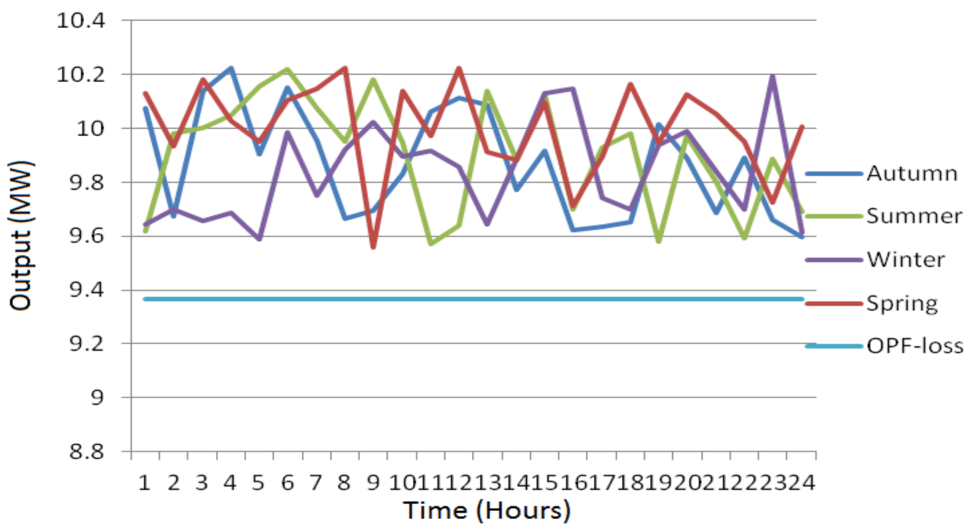


Fig 5 Losses with DGs when Consideration of Voltage Deviation as a Objectives.

Once sizes are tuned individualistically, the real power losses have amplified, as seen in the table 2 and 3. when each loss is enhanced autonomously, the sizes are also diverged from their ideal values. This shows that when one of the objectives in the CM issue is enhanced, the additional objective diverges from its ideal value. As a result, finding an ideal trade-off result among the opposing aims is possible.

*D. Results with Multi-Objectives*

Minimum and maximum value BMDG are shown in table 6 and figure 6 shows losses when considering all objectives.

Table 6 BM DG Capacities when Considering all the Objectives

| | Summer | Autumn | Winter | Spring |
|---|---|---|---|---|
| Minimum | 8.0396 | 8.119 | 8.1106 | 8.0468 |
| Maximum | 8.8113 | 8.9921 | 8.9723 | 9.0262 |
| Mean | 8.4893 | 8.5171 | 8.4587 | 8.4917 |
| Std Deviation | 0.284895 | 0.312733 | 0.309649 | 0.281632 |

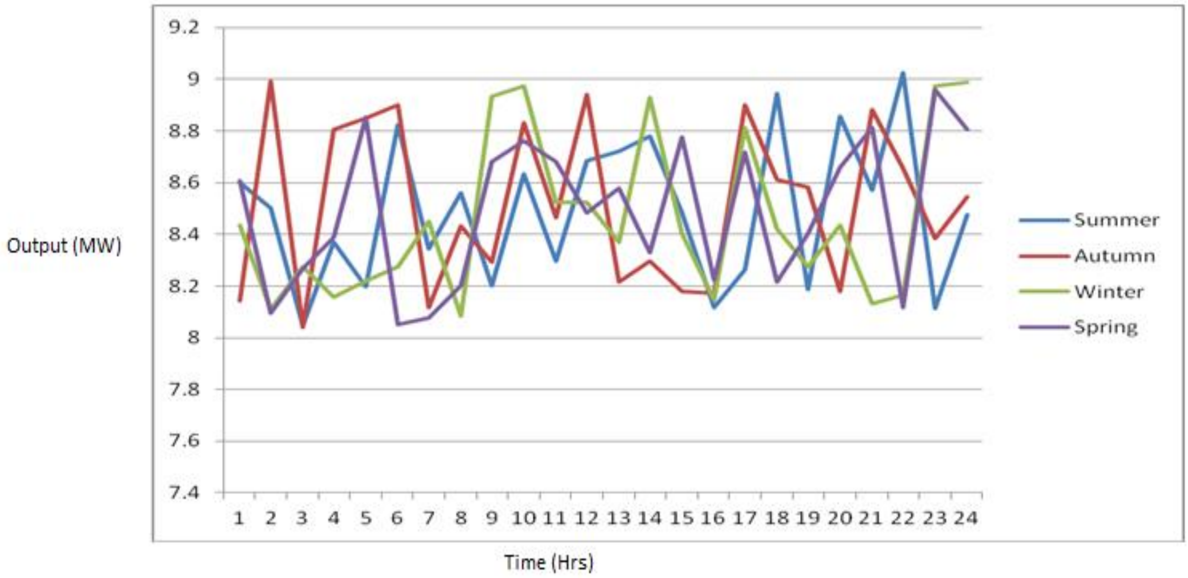

Fig 6 BMDG Capacity when all Objectives Consider

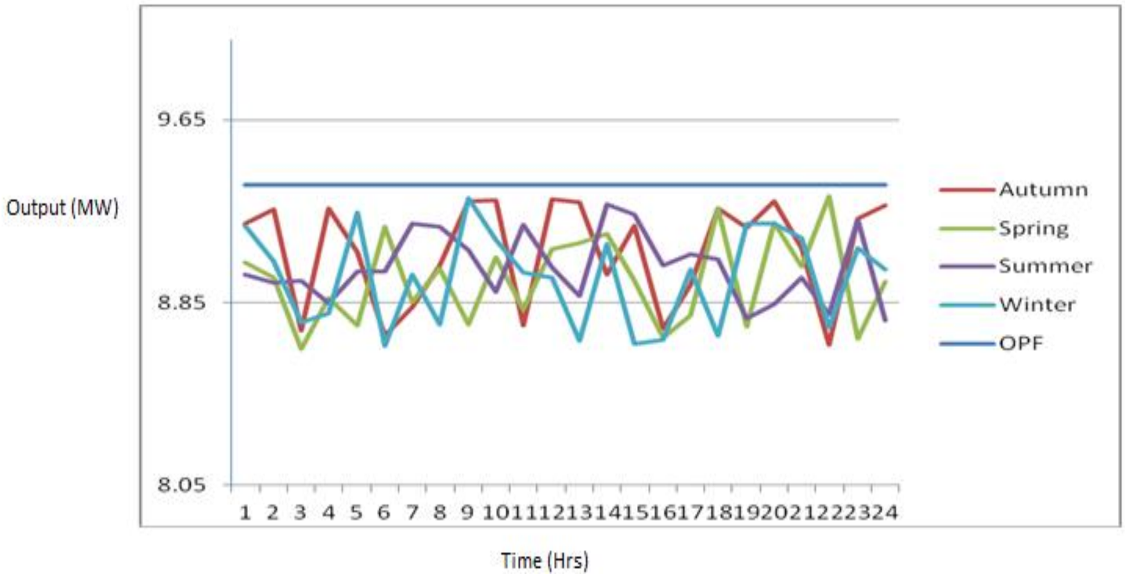

Fig 7 Losses when Consider all Objectives

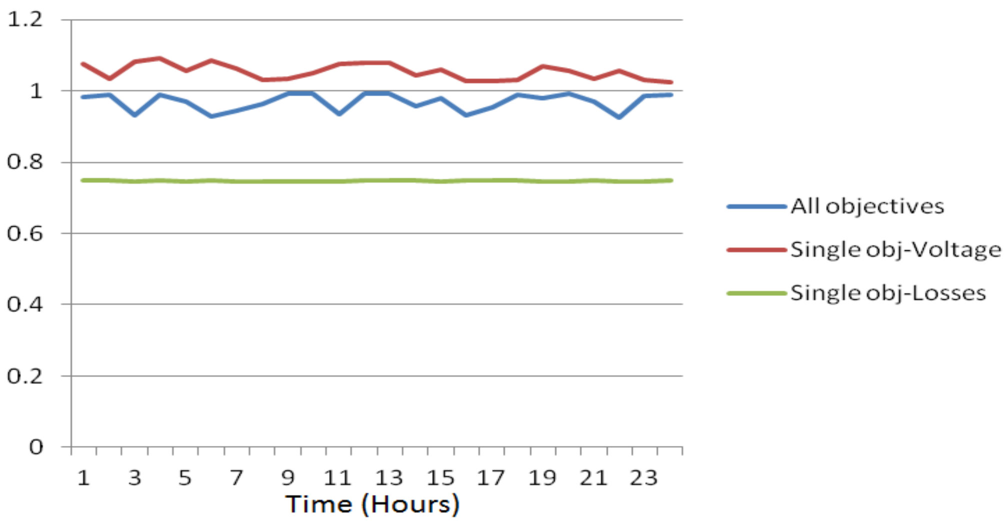

Fig 8 Loss Margin for Autumn Season with all and Single Objectives

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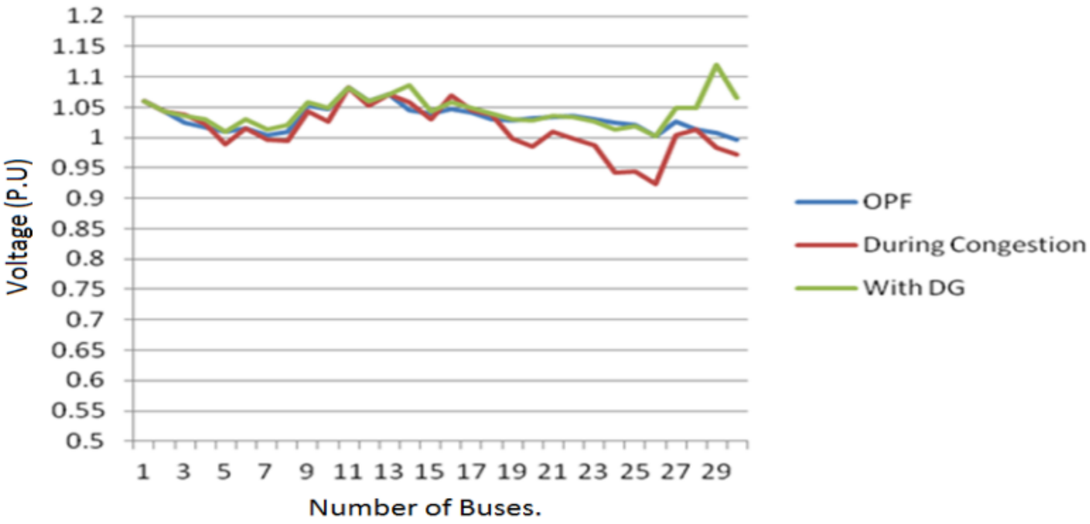


Fig 9 Voltage at Different Buses with and Without DG

It is observed from table 10 that in summer season BMDG capacity is less. Also Real losses are minimum 8.6481 MW. Figure 8 and 9 shows, loss margin for autumn season when considering single objective voltage deviation and loss minimization and multi-objectives and voltage at different buses with DG and without DG respectively. The overall results show that the advocated strategy is preferable in relieving network line congestion.

## VII. CONCLUSION

In this work, CM problem of transmission network has been pointed out and explained by integrating the optimum sizes of the biomass DGs with the consideration uncertainty of solar and wind renewable sources. To attain the best sizes of the DGs, multiple objectives are taken into account and combined into a single objective function. Grey wolf Optimization algorithm is used to get the best sizes of the DGs which are combined with current bulk power system. On a typical IEEE - 30 bus, the effectiveness of the suggested approach is evaluated. The comparison of the findings showed that the multi-objective approach that has been suggested and its technique for solving the problem is the best option for minimizing the power flows in the congested lines. Additionally, it can be said that in both test systems, the voltage profile and actual power losses have significantly improved along with the best use of DGs. Finally, it can be said that the suggested approach successfully reduces overcrowding and is readily transferable to real-time, complicated, non-linear optimization issues involving the power system.

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