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RESEARCH ARTICLE OPEN ACCESS

PLANNING OF DISTRIBUTED GENERATION SOURCES WIND AND PV IN IEEE 33-BUS SYSTEM

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ABSTRACT

To mitigate the impacts of rising power consumption and new technologies for distributed generation, microgrids are being developed. Another consequence of this is the expansion of the distribution network to include more microgrids, often known as multi-microgrid systems. Undoubtedly, renewable generators contribute to today's electrical energy networks. However, when it comes to scheduling, this might introduce uncertainty into the entities' mathematical models. Therefore, the future of a multi-day microgrid is planned using chance-constrained programming in this study. A system operating in an unpredictable setting. The traditional units are being utilized alongside the renewable energy units, which might have negative effects on the environment, such as increasing greenhouse gas emissions.

I. INTRODUCTION

Cost savings, improved economics, and environmental advantages from reduced greenhouse gas emissions have contributed to a rise in the adoption of renewable-based DGs in the last decade [1]. Using MGs (Microgrids) may solve a number of problems that this growth is causing in the functioning electrical power networks.

Anyway, as a result of the integration of a range of new technologies with MGs, their structures are growing more complicated, potentially exposing them to a slew of new issues, such as high investment costs, market challenges, and regulation challenges [2].

The advancements in technology section and industry, population expansion, and increasing economic comfort all contribute to a rise in energy use. Investments and planning based on accurate estimates are essential for the well-being and economics of both the producer and the consumer as energy demand rises [3].

Electrical energy consumption may be influenced by differences between developed and developing nations in socio-economic factors including population, energy exports and imports, and gross domestic product. For instance, studies comparing the established economy of the United States with that of Iran (a developing economy) found that, in 2030, Iran's EEC would be 2.73 times higher than in 2009, while the United States' EEC will be 1.09% lower [4].

In order to discover real-time optimum energy management solutions for a standalone hybrid wind-microturbine (MT) energy system, the particle swarm optimization algorithm (PSO) was used. PSO is a biologically driven direct search approach [5]. Unfortunately, the power flow limits and uncertainties were disregarded. Optimizing the control process of microgrid batteries while ignoring uncertainties and security limitations was also achieved by [6] by modifying the PSO algorithm for real-time optimum energy management.

According to [7] In order to control demand response and optimize costs, this study proposes a broad definition of the optimal operating strategy. To develop an energy management system for optimization objectives, a multi-period imperialist competition algorithm-based expert heuristic technique is used, but the network constraints are not taken into account. Also, the multi-layer ant colony optimization algorithm was used as a metaheuristic method to solve the day-ahead scheduling problem of microgrids.

Researchers are currently trying to pin down the exact advantages of metaheuristic techniques, such as their capacity to solve complicated issues and the optimality of the solutions they uncover. Consequently, methods such as mixed integer non-linear programming, liner programming, non-liner programming, mixed integer liner programming, mixed integer non-linear programming (LP, MILP, NLP, and MINLP) have been tested for energy management of isolated MGs in [8], ignoring the penetration of renewable-based distributed generation (DG) and uncertainties. In contrast, the authors of [9] addressed energy management on two levels: optimum power flow and unit commitment.

The biggest problem with these two books was that they didn't address the presence of uncertainty. Uncertainties in electrical power system are resulted because of load changing, solar radiation and wind speed variations which lead to unstable output power of the renewable energy power plants and problem was introduced under the name of stochastic programming optimization problem.

A plethora of models and methods, including CCP and the Resource-Based Model for Expected Value, were proposed to address this issue. A method for managing the energy consumption of a mixed-generation (MG) system that includes renewable power sources, batteries, diesel generators, and loads has been suggested in [10].

However, the limitations of the network and the unpredictability of renewable energy sources were disregarded in this study. In their study, the researchers from [11] introduced a microgrid system that uses combined heat and power units that are based on biomass.

The goal of the algorithm is to minimize operational costs by using an anticipated value model. Both electrical and thermal loads have been subjected to a demand response program in this issue. In this study, the computations have been done without the power flow limitations. With a limited model of the uncertainties and neglecting the network constraints [12] presented a mixed integer linear programming (MILP) method for energy management for MGs in the means of expected value form to model the uncertainties.

According to [13] Have introduced a fresh method for managing energy that makes use of updated mathematical models to account for a wide range of unpredictable demands. In order to determine the best operating points while taking into account diverse sources of uncertainty, stochastic scheduling for MGs with WTs, fuel cells as combined heat and power units, energy storage devices, and variable loads has been proposed [14]. For day-ahead scheduling of an MG disregarding security restrictions, a two-stage stochastic robust model-based optimization method was suggested in [15].

For energy management for the next day, the rigorous optimization may be too cautious. Using conditional value at risk, the authors of [16] provide a data-driven charging strategy for EVs that takes into account EV behavior and demand levels as sources of uncertainty. This approach has the potential to be refined for usage in MGs.

A different way to represent the unknowns is using Chance Constraints Programming (CCP), which solves all the issues mentioned. The optimization issue in CCP may be handled utilizing several ways that transform chance-constraints into deterministic ones, given a reliability level that is set for certain uncertain constraints [17].

As a result, CCP increases system stability and dependability by keeping the likelihood of breaching certain unknown requirements at the desired level. Solving nonlinear problems with uncertainty is also possible with the help of deterministic CCP counterparts. Stochastic power system challenges have so attracted the attention of several scholars who have used CCP. An optimization model for MG energy management that is data-driven and nonparametric is provided in [17]. Taking into account network and security limits might enhance the value of the job, notwithstanding the noble intentions.

The presence of greenhouse gases in the atmosphere is typically responsible for the emergence of environmental concerns over global warming, which is now one of the most pressing issues facing our planet. It is important to reduce the use of traditional units and replace them with cleaner manufacturing methods in order to reduce emissions. Therefore, a penalty cost associated with emissions has been taken into account in several researches. In [18], the authors provide a CCP-based methodology for managing the energy consumption of MGs that are linked to the grid. The authors have made nice work with this reference; however the research may be much better if they took into account energy storage devices and network restrictions, two crucial tools in MGs. For power system planning, [19] have laid out a multi-stage CCP framework to help in dealing with various types of uncertainty.

The researchers in [20] proposed an improved particle swarm optimization (PSO) algorithm is proposed to solve a multi-objective optimal load dispatch model of microgrid with the stochastic access of electric vehicles. Then they have discussed the dispatch results under three different scheduling scenarios, i.e., uncoordinated charging scenario, coordinated charging scenario with and without DGs.

The task will be of higher quality if many microgrids are considered. Additionally, a multi microgrid system is a high-level structure that is formed by the presence of several dispersed generating units and loads in the distribution system. In [21], a hybrid stochastic-robust framework for MMGs system optimum scheduling is suggested. Energy management takes both the current and future cost of energy into account.

As an additional tool for improved MG operation, time-of-use demand response programs are being considered. Stochastic programming is also used to simulate energy pricing, electric cars, PV systems, WTs, and other sources of uncertainty. In order to minimize the overall cost of the system, which includes the cost of power generation by units as well as the cost of power exchange among the interconnected MGs and the main grid, the authors of this research have presented a new stochastic framework for optimal energy management of interconnected MGs [22].

One method for managing energy in MMG systems that takes contingencies into account is shown in [23]. This method takes the possibility of a contingency into account and uses energy management as a tool for addressing MMG-style contingency situations. Energy management of MMG-based DNs in the context of demand response programs and uncertainties related to renewable energy supplies, loads, and pricing is addressed in a new way by the authors of [24].

We use a meta-heuristic method called NSGA-II to solve the energy management issue, which is modeled as a multi-objective problem. The authors of [25] laid forth a unified strategy for managing energy consumption in MMG systems. In this paper, a novel metric is proposed for evaluating energy management procedures in conditions of uncertainty, including those involving load, WTs, and PV systems.

We can summaries the conclusion of the previous works in the following points:

- The ignorance of uncertainties caused by wind and solar units and load changes.

- Power flow constraints was not included in the calculations in one paper.
- Network and security constraints of have been ignored.
- Only the presence of one MG has been studied in most of the studies.

As a conclusion there is no research that took into account the uncertainties resulted by load, PV and wind turbines with the emission consideration in multi microgrid systems in solving the day-ahead scheduling problem using chance constrained programming approach.

II.MATHEMATICAL MODELING OF THE SYSTEM

Within microgrids are one or more kinds of distributed energy (solar panels, wind turbines, combined heat and power, generators) that produce its power. In addition, many newer microgrids contain energy storage, typically from batteries. Some also now have electric vehicle charging stations Figure 1.

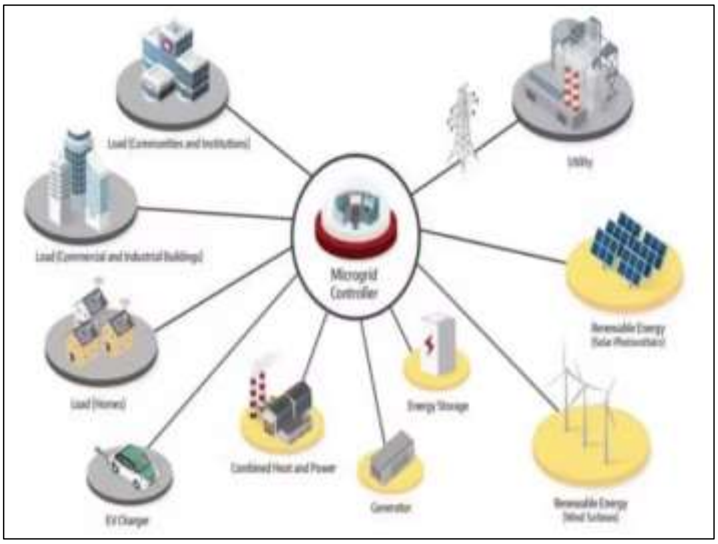


Figure 1: Microgrid scheme.
Source: Authors, (2025).

II.1 INTERNAL COMBUSTION GENERATORS:

The internal combustion (IC) unit technology transforms the fuel-based source of energy into electricity. The production costs are calculated as a quadratic function of the output power of the unit P during a time period t.

$$Cost_{IC,t}^{operation} = \alpha_1 P_{IC,t}^2 + \alpha_2 P_{IC,t} + \alpha_3 \tag{1}$$

Where:

α_1, α_2, α_3 Cost function coefficients of diesel generator, besides to the operation cost there is the unit startup cost:

$$Cost_{IC,t}^{stup} = \gamma_{IC,t} \times C_{IC}^{SU} \tag{2}$$

Where:

γ First, the total cost, followed by a binary variable representing the unit's status:

$$Cost_{IC,t} = Cost_{IC,t}^{operation}(P_{IC}) + Cost_{IC,t}^{stup} \tag{3}$$

The complicated power limits and the ramp up pace of the generating units are the limitations of these sorts of units:

$$0 \le P_{IC,t} \le v_{IC,t} P_{IC}^{max} \quad v_{IC,t} \in 0,1 \tag{4}$$

$$-ramp_{IC} \times P_{IC}^{max} \le P_{IC,t} - P_{IC,t-1} \le ramp_{IC} \times P_{IC}^{max} \tag{5}$$

$$P_{IC,t}^2 + Q_{IC,t}^2 \le S_{IC}^2 \tag{6}$$

II.2 WIND GENERATORS

When it comes to harnessing renewable energy sources for electrical power, wind production units are among the most exciting and rapidly evolving technology. They include wind turbines, which convert the wind's kinetic energy into electricity. Because its output power is dependent on the wind speed, an inherently stochastic variable, the amount of electrical energy that is produced is never guaranteed.

Below is an example of how the wind speed follows a Weibull PDF, which uses two WT-site characteristics, called the shape factor and the scale factor:

$$f_V(v) = \left(\frac{k}{\delta}\right)\left(\frac{v}{\delta}\right)^{k-1} e^{-\left(\frac{v}{\delta}\right)^k} \quad 0 \le v \le \infty \tag{7}$$

The following shows the relationship between wind speed and the electrical power produced by the wind system:

$$P_{wt} = \begin{cases} 0 & v \le v_{in}, \quad v \ge v_o \\ \frac{v - v_{in}}{v^{rated} - v_{in}} P_{wt}^{rated} & v_{in} \le v \le v^{rated} \\ P_{wt}^{rated} & v^{rated} \le v \le v_o \end{cases} \tag{8}$$

II.3 SOLAR POWER GENERATION

One of the most prevalent and straightforward methods of generating renewable energy is the use of photovoltaic (PV) devices to convert sunlight into electricity. The rapid expansion of PV panel installations may be attributed to their compact design and reduced price tag as compared to WTs.

Solar irradiance is a stochastic phenomenon that affects the power output of PV systems. This relationship is often represented by the lognormal PDF, which looks like this:

$$f_{Ir}(Ir) = \frac{1}{Ir\,.\sigma\,.\sqrt{2\pi}} exp\left[\frac{-(lnIr - \mu)^2}{2\sigma^2}\right] \quad I_r \ge 0 \tag{9}$$

Depending on the amount of sunlight reaching the PV system, its output power is proportional to the following:

$$P_{PV} = \begin{cases} P_{PV}^{rated} \times \left(\frac{Ir^2}{Ir_{std}\,.Ir_{cer}}\right), & Ir \le Ir_{cer} \\ P_{PV}^{rated} \times \left(\frac{Ir^2}{Ir_{std}}\right), & Ir_{cer} \ge Ir \end{cases} \tag{10}$$

II.4 ENERGY STORAGE SYSTEM

Energy storage system is considered as a battery, charging and discharging power limitations:

$$0 \le P_{ch,t}^{bat} \le v_{ch,t}^{bat} P_{cap}^{bat} \tag{11}$$

$$0 \le P_{disch,t}^{bat} \le v_{disch,t}^{bat} P_{cap}^{bat} \qquad (12)$$

The limitation on not charging and discharging at the same time:

$$v_{ch,t}^{bat} + v_{disch,t}^{bat} \le 1 \quad v_{ch,t}^{bat}, v_{disch,t}^{bat} \in 0,1 \qquad (13)$$

Battery system limitations with respect to charge or energy level:

$$SOC_t = SOC_{t-1} - \frac{1}{P_{cap}^{bat}}\left(P_{disch,t}^{bat} - P_{ch,t}^{bat}\right) \qquad (14)$$

$$0 \le SOC_t \le 1 \qquad (15)$$

$$SOC_{T_0} = SOC_{int} \qquad (16)$$

$$SOC_{T_{final}} = SOC_{final} \qquad (17)$$

The stored/released power constraints:

$$P_t^{bat} = P_{ch,t}^{bat} - P_{disch,t}^{bat} \qquad (18)$$

II.5 LOADS

One source of uncertainty in electrical power system modeling is loads, which are a result of users' stochastic behavior. When trying to model the load's uncertainty, the normal distribution function is often used:

$$f_{load}(load) = \frac{1}{\sigma.\sqrt{2\pi}} exp\left[\frac{-(load - \mu)^2}{2\sigma^2}\right] \qquad load \ge 0 \qquad (19)$$

II.6 NETWORK MODELING

Radial networks are the standard representation for MGs and distribution systems. Assumption #1 in this thesis is that Bus #1 is upstream-connected to the grid and has a 1 P. u. apparent power flexible power injection:

$$S_{k,t} = S_{k,t}^{bat} + S_{k,t}^{load} - S_{k,t}^{gen} \qquad (1)$$

II.7 EMISSION MODELING

May learn how much pollution a typical unit produces as a function of fuel used by looking at the following equation:

$$Em_{IC,t} = \Psi_{IC}.\frac{Cost_{IC,t}^{operation}}{\xi_{fuel,IC}} \qquad (21)$$

The emission coefficient:

$$\Psi_{IC} = PTV_{IC}.EC_{IC}.OC_{IC} \qquad (2)$$

Where: PTV: Pure thermal value, EC: Emission factor OC: Oxidation factor

To calculate the emission cost the amount of emission is multiplied to a penalty factor ħ:

$$Cost_{IC,t}^{emission} = ħ_{IC} \times Em_{IC,t} \qquad (23)$$

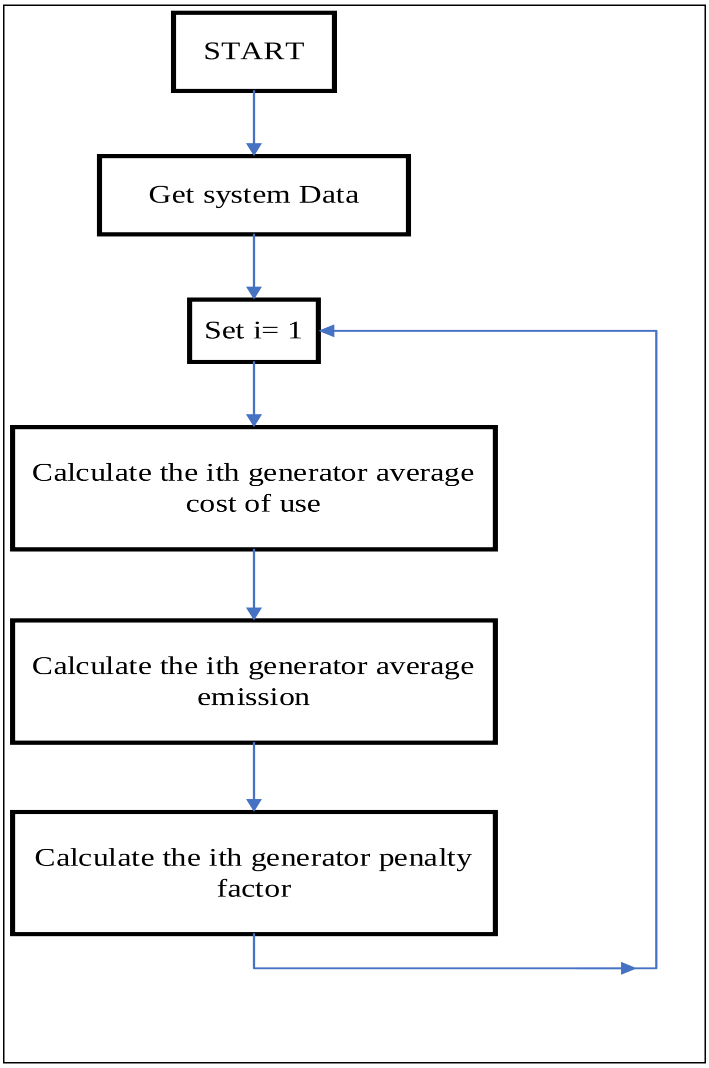


Figure 2: calculating penalty factor algorithm.
Source: Authors, (2025).

Objective function:

$$min\, O.F._{MG,\omega} = \sum_{t=T_0}^{T_f}\Big(\sum_{IC=1}^{n_{IC,\omega}}\left[Cost_{IC,t} + Cost_{IC,t}^{Emission}\right] + \lambda_t^{buy}.P_{\omega,t}^{sh} - \lambda_t^{sell}.P_{\omega,t}^{sur}\Big) \qquad (24)$$

Simulation results

The electrical energy prices in the distribution network estimated in $ for MWh are shown in Figure 3.

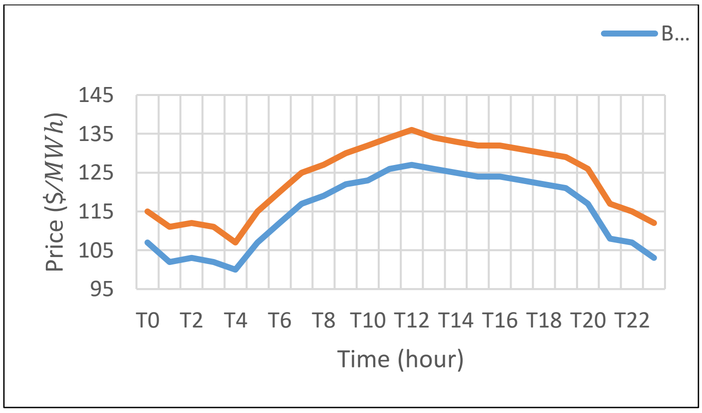
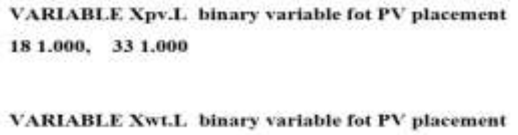
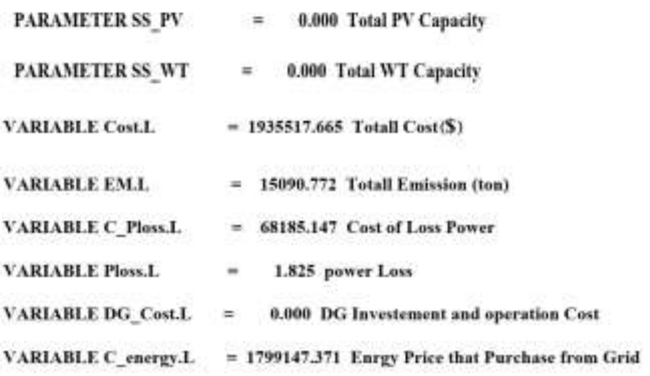


Figure 3: Electrical energy prices.
Source: Authors, (2025).



```
VARIABLE Xpv.L  binary variable fot PV placement
18 1.000,    33 1.000


VARIABLE Xwt.L  binary variable fot PV placement
```

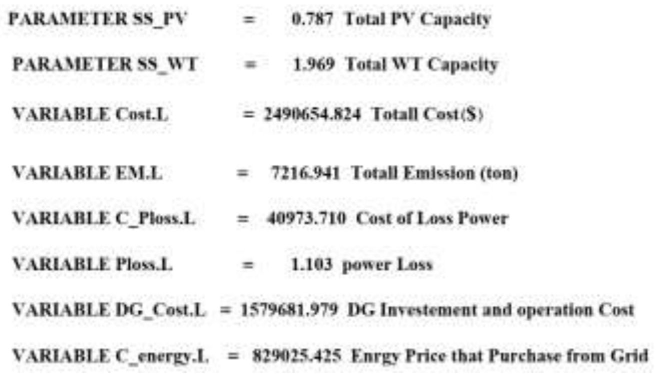
In the simulation of the deterministic case the distributed generation units weren’t taken into account. The results for this simulation:



```
PARAMETER SS_PV        =     0.000  Total PV Capacity

PARAMETER SS_WT        =     0.000  Total WT Capacity

VARIABLE Cost.L          = 1935517.665  Totall Cost($)

VARIABLE EM.L            =    15090.772  Totall Emission (ton)

VARIABLE C_Ploss.L       =    68185.147  Cost of Loss Power

VARIABLE Ploss.L         =       1.825  power Loss

VARIABLE DG_Cost.L      =      0.000  DG Investement and operation Cost

VARIABLE C_energy.L      = 1799147.371  Enrgy Price that Purchase from Grid
```

According to the above results the losses in one day are 1.825 MWh and the cost of these losses is 68185.1 dollars. The amount of pollution emission related to the power purchased from the grid in one year is 15090 tons and the cost of buying energy from the net for one year is 1799147 dollars. For this case the voltage range for the busses in every hour is shown in Fig. 4. In this figure every curve is related to one hour of the day. It’s clear that the worst case for the voltage value 0.918 pu. The amount of the purchased power from the net in every hour is depicted in Fig. 5, and it can be noticed that the maximum limit is equal to 3.8 MW in the hour 17.

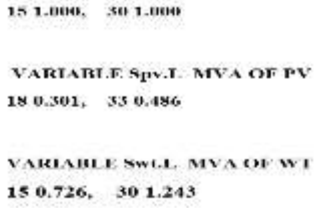
The second case is related to the uncertainty case. The results of this case are as follow. And it’s clear that in this case a 0.787 MVA PV and a 1.969 MVA WT are installed.



```
PARAMETER SS_PV        =     0.787  Total PV Capacity

PARAMETER SS_WT        =     1.969  Total WT Capacity

VARIABLE Cost.L          = 2490654.824  Totall Cost($)

VARIABLE EM.L            =    7216.941  Totall Emission (ton)

VARIABLE C_Ploss.L       =    40973.710  Cost of Loss Power

VARIABLE Ploss.L         =       1.103  power Loss

VARIABLE DG_Cost.L  = 1579681.979  DG Investement and operation Cost

VARIABLE C_energy.L    =  829025.425  Enrgy Price that Purchase from Grid
```

In this case the energy loss in one day is equal to 1.103 MWh which is 40 % decreased compared to the previous case (without DG). The amount of pollution in one year has also reached 7216 tons, which has decreased by 52% compared to the previous situation. The cost of exchanging energy with the grid in one year is 829025 dollars, which has decreased by 53% compared to the previous state.

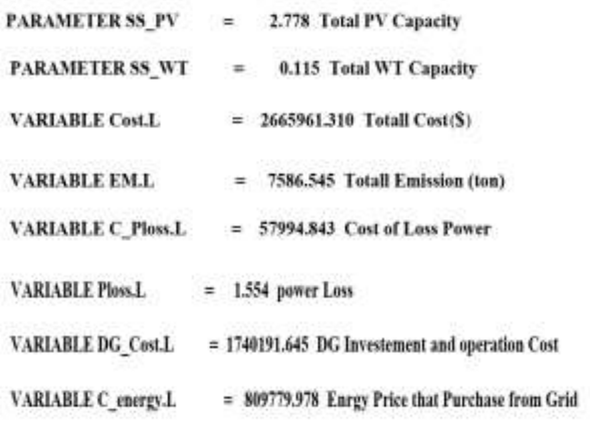
In this case, the location and capacity of PV and WT sources are obtained as follows. It is clear that two PVs are installed in 18 and 33 buses and two wind turbines are also installed in 15 and 30 buses. The capacities are also stated below that for PV it is equal to 0.301 and 0.486 megavolt ampere (MVA) respectively. For wind turbine capacities are 0.726 and 1.243 megavolt ampere.



```
15 1.000,    30 1.000


VARIABLE Spv.L  MVA OF PV
18 0.301,    33 0.486


VARIABLE Swt.L  MVA OF WT
15 0.726,    30 1.243
```

For this case, the bus voltage range is shown in Fig. 6 and the amount of power exchanged with the network is shown in Fig.7. Is. It is clear that the minimum voltage range is equal to 0.95 pu, which is improved compared to before. The maximum power received from the network is also 2.6 megawatts, which shows a decrease of 1.2 megawatts compared to the previous state.

And finally, the uncertainty of the PV and WT is taken into account, 2.778 MVA PV and 0.115 MVA WT were installed. The amount of installation Scattered production has not changed significantly compared to the previous state, but the amount of PV installation has increased and the amount of turbine installation has increased Badi is greatly reduced. The reason for choosing more PV is also due to the coincidence of its production hours with peak demand which makes its uncertainty management easier than wind turbine.

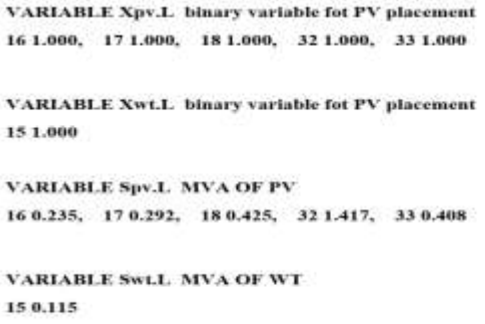


```
PARAMETER SS_PV        =     2.778  Total PV Capacity

PARAMETER SS_WT        =     0.115  Total WT Capacity

VARIABLE Cost.L          =  2665961.310  Totall Cost($)

VARIABLE EM.L            =    7586.545  Totall Emission (ton)

VARIABLE C_Ploss.L       =   57994.843  Cost of Loss Power

VARIABLE Ploss.L       =   1.554  power Loss

VARIABLE DG_Cost.L     = 1740191.645  DG Investement and operation Cost

VARIABLE C_energy.L      =  809779.978  Enrgy Price that Purchase from Grid
```

In this case, the loss is equal to 1.554 megawatts, which is 15% compared to the first case (without DGs). The amount of contamination in one year has also reached 7586 tons, which has decreased by 49% compared to the first case.

The cost of exchanging energy with the network in one year is 809779.9 dollars, which has decreased by 54% compared to the first case.

In this case, the location and capacity of the resources are obtained as follows. It is clear that 5 PV in buses 16, 17, 18, 32 and 33 are installed. The capacities of these resources are respectively 0.235, 0.292, 0.425, 1.417 and 0.408 MVA. One wind turbine is also installed in bus 15 with a capacity of 0.155 megavolt ampere.



```
VARIABLE Xpv.L  binary variable fot PV placement
16 1.000,    17 1.000,    18 1.000,    32 1.000,    33 1.000


VARIABLE Xwt.L  binary variable fot PV placement
15 1.000


VARIABLE Spv.L  MVA OF PV
16 0.235,    17 0.292,    18 0.425,    32 1.417,    33 0.408


VARIABLE Swt.L  MVA OF WT
15 0.115
```

For this case, the average voltage range of the buses is shown in Fig. 8. Based on this figure the minimum voltage range is equal to 0.96 pu, which is improved compared to the first case. Also, the amount of energy exchanged with the network every hour and every scenario are shown in Fig. 9. From this figure we can notice that from hour 7 to 20 when PV sources produce power, the amount of energy exchanged with the grid is also decreased. The maximum amount of demand from the network is 2.8 megawatts, which is a decrease compared to the first case (1MW).

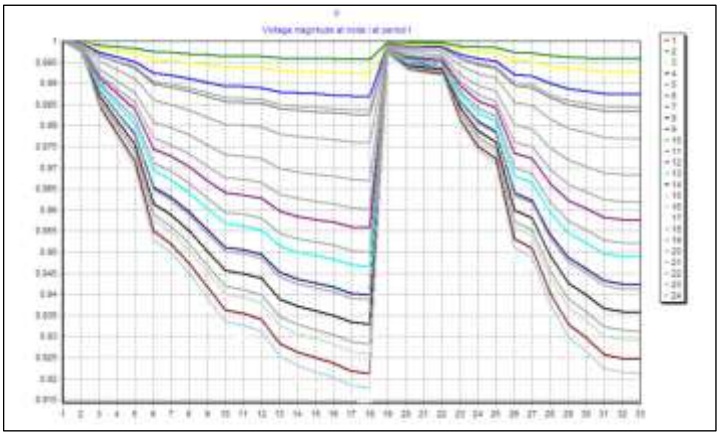


Figure 4: Voltage range of each bus per hour for deterministic case without distribution generation.
Source: Authors, (2025).

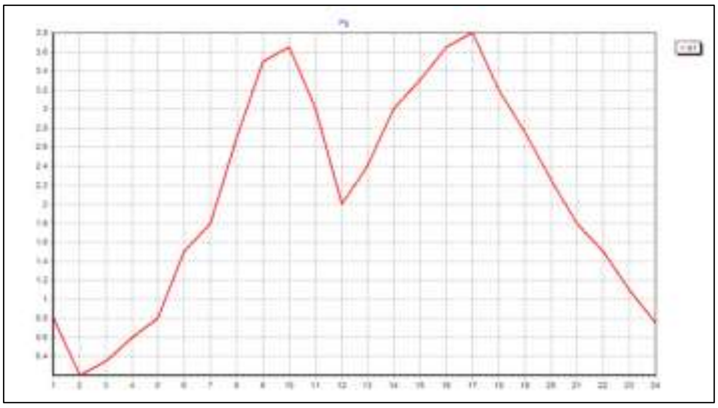


Figure 5: The amount of energy purchased from the grid every hour.
Source: Authors, (2025).

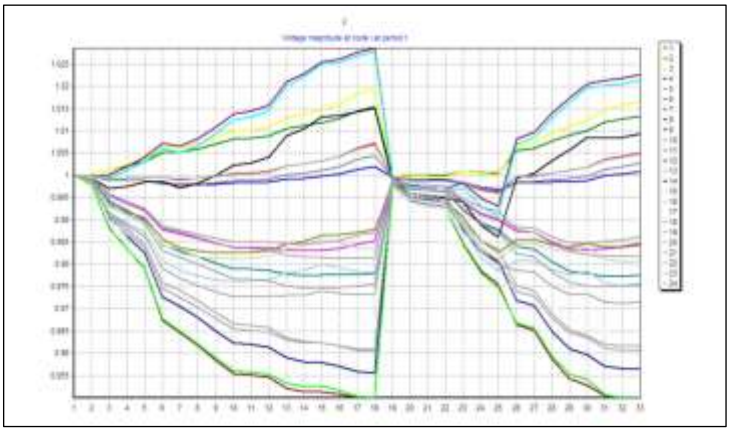


Figure 6: Voltage range of each bus per hour for deterministic case without distribution generation.
Source: Authors, (2025).

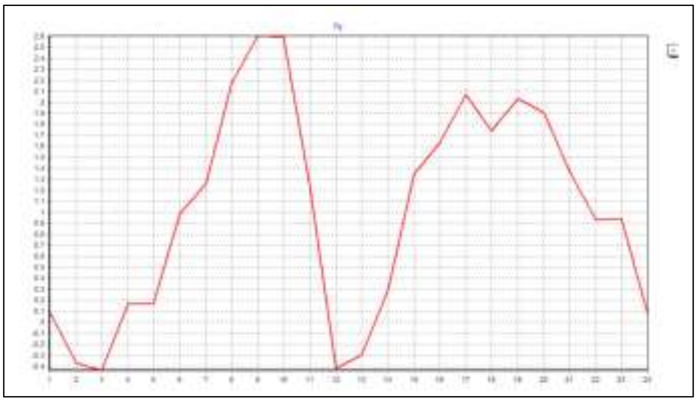


Figure 7: The amount of energy purchased from the grid every hour in the deterministic case.
Source: Authors, (2025).

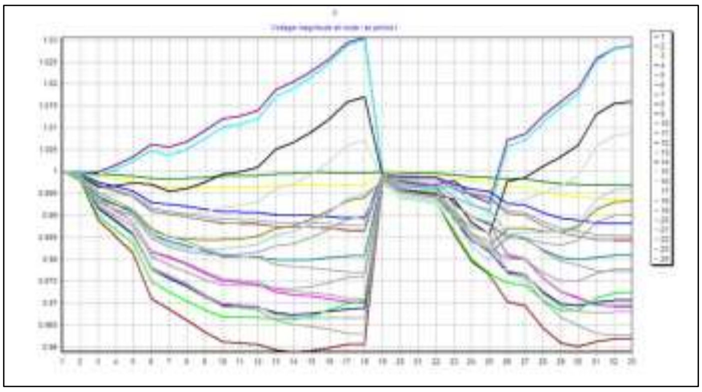


Figure 8 Average voltage range of each bus per hour for contingency mode.
Source: Authors, (2025).

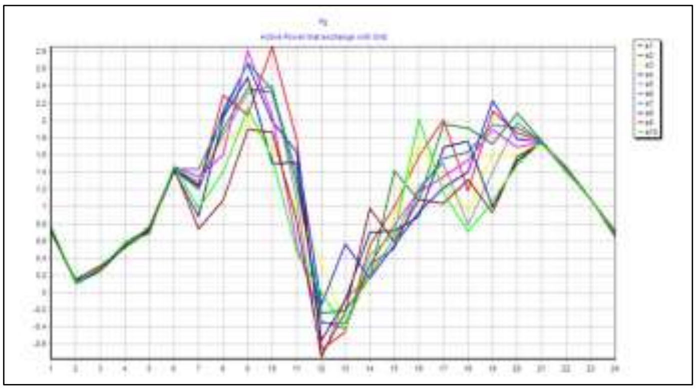


Figure 9: The amount of energy exchanged with the network per hour and per scenario for the probability case.
Source: Authors, (2025).

V. CONCLUSION

All the researches and the results of this work indicates to the increasing importance of the renewable energy. And the new electrical system which includes the microgrid (MMG system in the case of many MGs) is associated with more complicated energy management problems. In this work a day ahead scheduling of a 33-bus system containing 3 microgrids with renewable resources PV and wind turbine optimization problem was solved using GAMS software in 3 cases: deterministic, and with renewable energy penetration in tow levels.

The results show that the more penetration of the renewable energy the total cost and the energy purchased from the network decrease besides to the pollution reduction. So, the only problem is the associated difficulty in the energy management calculation which can be solved using the powerful optimization algorithms and software. A linearization to represent the issue as a linear problem and find a global optimum is proposed for use in future investigations. Additionally, it may be very intriguing for future research to suggest a method of bidding for the MMG system that takes emissions and CCP modeling into account. To further improve optimization while protecting MG privacy, a decentralized approach to the issue in a CCP context should be considered.

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