RESEARCH ARTICLE OPEN ACCESS

Optimization of a Micro Grid Operation under Uncertainty Using Model Predictive Control

Omo-EgbekuseNosawema*, Nwabueze Charles Nnaemeka**, Prof. I.I. Eneh***
Electrical and Electronics Engineering Department, Enugu State University of Science and Technology, ESUT, Enugu
Email; nosawemas_mail@yahoo.com

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Abstract:
This research work shows the optimization under uncertainty conditions using a Model Predictive Control (MPC) technique on a Microgrid.Using this approach; characterizing the Microgrid Operation; determining the threats in the microgrid operation; designing a Model Predictive Controller rule base that will eradicate the threats in micro grid operation thereby enhancing its operation; training Artificial Neural Network (ANN) in this rule base for effective eradication of its operational threats thereby enhancing its operational efficiency; designing a Simulink model for optimization of a micro grid operation under uncertainty using model predictive control, validating and justifying the operational efficiency of a microgrid with and without MPC are the main sequence.A simulation of the Power System stabilities of the microgrid operation obtained using different optimization techniques is presented a comparison and analysis of the results obtained with and without MPC is shown to illustrate the effectiveness of MPC.Utility companies can apply this technique to microgrids being developed for improved performance.

Keywords —**Micro grid, Model Predictive Control (MPC), Artificial Neural Network (ANN)**

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I. INTRODUCTION

A micro-grid is defined as a cluster of distributed generation (DG), distributed storage (DS) and loads, serviced by a distribution system, and can be operated in either islanded or grid-connected mode *Katiriaei et al, 2008*. DG within micro-grids includes photo-voltaics (PVs) and wind turbines (WTs). DS units are mainly batteries. Sound operation of a micro-grid requires an Energy Management Strategy (EMS).

The essential problem of EMS is energy balance by coordinating power among the Distributed Energy Resources (DER) units in order to supply the loads with required energy in real time.

There are two approaches for the developmentof micro-grid energy management. The first one is thecentralized approach, which ensures economic operation andmaintains the balance between the power production and consumption*Gambino et al, 2014*. To this end, Model Predictive Control (MPC)is an effective control policy for multi micro-grids whichcan handle the uncertainties between supply and demand aswell as the system constraints, such as generator capacityand ramp rate. *Xie et al, 2009.*

The second approach for micro-grid energy management isthe distributed control architecture, which is efficient, scalable and privacy preserving, especially for multi micro-grids with large size *Parisio et al, 2017.*

Problem statement

The problem of instability in power supply has led to liquidation of some companies because they could not meet other financial challenges like paying workers' salaries, buying raw materials and other financial obligations. The primary cause of not meeting customers demand and other financial challenges is as a result of instabilityof power supply from the grid. The cause of instability of power supply is as a result of not having an alternative power supply to enhance power stability. This problem of instability of power supply observed throughout the nooks and crannies of the federation can be overcome by introduction of optimization of the micro grid operation under uncertainty using model predictive control.

Research Aim and objectives

The aim of this work is to realize optimization of a micro grid operation under uncertainty using model predictive control.

The objectives are to:

i. characterize the microgrid operation
ii. Determine the threats in micro grid operation.
iii. Design a model predictive controller rule base that will eradicate the threats in micro grid operation.
iv. train artificial neural network (ANN) for effective eradication of threats
v. Design a Simulink model for optimization of the micro grid operation under uncertainty using model predictive control.
vi. Validate and justify the operational efficiency of the micro grid with and without MPC.

Significance of the study

i. It enhances stable power supply.
ii. It encourages investors to build industries and factories.
iii. It enhances the Gross Domestic Product (GDP)&economic status of the nation.
iv. It reduces rate of unemployment.
v. It improves quality of life of citizens.
vi. It reduces the crime rate.
vii. It aids technological development.
viii. The poverty rate would reduce.

Scope and limitation of study

This work covers mainly stabilizing power supply in optimization of a hypothetical micro grid operation (as presently there are no microgrids fully operational in the country) under uncertainty using model predictive control using data obtained from a suitable community.

Also,it does not deal on the initiation and physical development of a new microgrid project as this research was based on simulation. For such, a more comprehensive Environmental Impact Assessment (EIA) would be required.

II. MATERIALS AND METHOOD

Material

The materials used for this project include;

i. Computer System
ii. MATLAB& Simulink software
iii. Proteus software.

Methodology

Characterizing the microgrid operation

Microgrid can be wind or solar pending on the one the researcher has wittingly chosen to embark on and the geographical location of such areas. In this case Amoli in Enugu state is a suitable area to execute such project since wind and solar are in abundance in Amoli. I looked up the meteorological report of Amoli and Awgu, to verify whether it can sustain the project at hand.

From my findings the annual average wind speed in Amoli is 6m/s. A hill called "Ugwuekude" in Amoli is a good site for this project. Average sunshine of 8 hours daily (8am to 4pm) is observed there too.

Analysis of the energy demand for a cluster of building/facilities in Amoli community

The questionnaire for investigating house hold loads was distributed to all the households to determine the energy demand for each building. From my findings we have an average load of 500kW to cover. The renewable energy in this project can generate 600kW thereby having a tolerance of 100kW. The minimum to maximum load found per house hold ranges from 300watts to 3000watts. The number of households that have load above 1500watts is almost half the total population of the entire town.

TABLE 1: PEAK LOAD ON 33KV AND 11KV FEEDERS IN AMECHI DISTRICT

APRIL 2017	TR3 MVA	TR4 MVA	AGBANI	AWGU	ITUKU	UDI
	12.50MW	9.7 MW	4.5 MW	5.4 MW	5.39 MW	3.75 MW
33kV	**AGBANI**	**AWGU**	**ITUKU**	**UDI**	**NKWO**	
	0.4 MW	8.7 MW	15.8 MW	14.9 MW	9.6 MW	68.44 MW
MAY 2017	**TR3 MVA**	**TR4MVA**	**AGBANI**	**AWGU**	**ITUKU**	**UDI**
	10MW	10.63MW	4.85MW	4.85	3.93	3.75
33kV	**AGBANI**	**AWGU**	**ITUKU**	**UDI**	**NKWO**	
	0.5MW	15MW	11.3MW	15MW	7.7MW	66.88 MW
FEB 2017	**TR3 MVA**	**TR4 MVA**	**AGBANI**	**AWGU**	**ITUKU**	**UDI**
	9.20MW	9.85MW	5.2MW	4.92MW	4.27MW	4.64 MW
33kV	**AGBANI**	**AWGU**	**ITUKU**	**UDI**	**NKWO**	
	0.5MW	6.6MW	14.9MW	13.60	10.60MW	46.21 MW
	0.5MW	6.6MW	14.9MW	13.60MW	10.60MW	65.32 MW

Table 2

S/N	FEEDER NAME	ENERGY IMPORTED (KWH)	ENERGY BILLED (KWH)	ENERGY LOSS (KWH)	REVENUE BILLED (N)	CASH COLLECTED (N)
A	B	D	E	F=D-E	G	H
	AGBANI	3.9MILLION	3.2MILLION	0.7MILLION	76.71MILLION	73.11MILLION
	AGWU	2.8MILLION	2.4MILLION	0.4MILLION	66.70MILLION	62.21MILLION

The parametric data in Table1 was gotten from EEDC Amaechi that suppliesAwgu, Agbani, Ituku, Udi and Ngwo.

Amoli town could not experience consistent power supply from the grid which was the reason renewable power was incorporated to the grid. There is an 11kV feeder that enters the town and terminates at the boundary of the town with the neighbouring town. There is no continuation of the feeder to the neighbouring town so as to prevent power loss to other town. The neighbouring town is fed through another route. Ugwuekude is the load centre of Amoli. The average wind speed there is 6m/s and average daily sun shine is 8 hours (8am to 4pm).

Table 3 Empirical data for grid and renewable Energy stability

Time	**Conventional empirical data for grid and renewable energy stability**
1	0.3
2	0.3
3	0.3
4	0.3
5	0.3
6	0.4
7	0.4
8	0.4
9	0.4
10	0.3
11	0.3
12	0.3

The parametric data collected from EEDC as shown in the above table was used for the optimization.

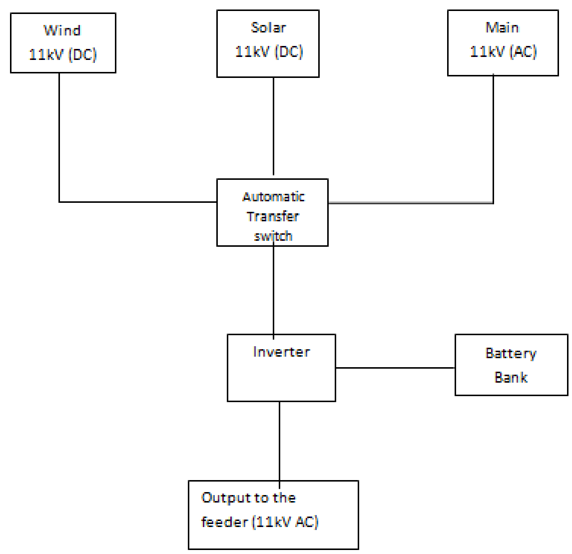

Fig .1: Block Diagram ofthe Micro grid

Battery Bank

190 pieces of 2V 200A connected in series = 380V/200A. It is then connected in parallel to give 380V/400A.

Solar panels

44 panels at 250watts each were used to get 11kV DC. The current rating of each 250watts is 10.59A.(250watts 23.6constant value) 10.59 x 44 = 466A. It is connected in series parallel to maintain the current. A total of 88 panels were used.

Wind turbine

The capacity of wind turbine used was rated 11kV/500A.

Optimizing the energy demand for a cluster of building facilities in Amoli

Two renewable sources wind, solar and grid of EEDC district inEnugu have two peak loads of A and B that require power P1 and P2. Each unit of type A require 0.5MW of P1 and 6.6MW of P2.Type B requires 6.6MW of P1 and 0.5MW of P2 (Each unit).The company has only 46.21MW of P1 and 65.32MW of P2. Each unit of type A brings a profit of #73.11M and each unit of type B brings a profit of #62.21M. Formulate the optimization problem to maximize profit for optimization of a micro grid operation under uncertainty using model predictive control.

The parametric data obtained from EEDC was used for the optimization.

SOLUTION

Table 4: Optimization table obtained from the parametric data

Power	P1 (MW)	P2 (MW)	Profit (#)
A	0.5	6.6	73.11
B	6.6	0.5	62.21
	46.21	65.32	

Decision variable:

The decision variables are power A and B. Thus, let the number of power A be x while that of B is y.

Objective function: The given problem is aimed at maximizing profit.

Let Z be the objective function profit of each unit of type A = #73.11, that is profit of x unit of type A = #73.11x.

Profit of each unit of type B = 62.21, that is profit of y unit of type B = #62.21y.

Total profit = 73.11x + 62.21y 3.1

Constraints (i): Company has only 46.21MW of P1

Unit of A requires 0.5MW of P1, that is x-unit requires x-MW of P1.

1 unit of B requires 0.5MW of P1.

Thus y-unit requires 0.5y-MW of P1

Thus, total available quantity of P1 for A and B = 46.21MW

Therefore

$0.5x + 6.6y \leq 46.21$ 3.2

Constraint (ii): Company has only 65.32MW of P2.

1 Unit of A requires 6.6MW of P2.

Thus x- unit requires 6.6x – MW

1 Unit of B requires 0.5MW of P2.

Thus y – units requires y – MW.

Total available quantity of P2 for A and B = 65.32MW.

That is

$6.6x + 0.5y \leq 65.32.$ 3.3

Constraint (iii): Supply of A and B cannot be negative, that is x >= 0 and y >= 0

The mathematical model formulation for optimization of a micro grid operation under uncertainty using model predictive control

Maximize $Z = 73.11x + 62.22y$ 3.4

Subject to $0.5x + 6.6y \leq 46.21$ 3.5

$6.6x + 0.5y \leq 65.32$ 3.6

$x \geq 0$ and $y \geq 0$

Then use simplex method to solve the mathematical model of the equations 3.2.4, 3.2.5 and 3.2.6

$z = 73.11x + 62.22y$ 3.7

$0.5x + 6.6y \leq 46.21$ 3.8

$6.6x + 0.5y \leq 65.32$ 3.9

Equate equation 3.2.7 to zero and remove all the constraints in the equations 3.2.8 and 3.2.9 respectively by introducing slacks

$Z - 73.11x - 62.22y = 0$ 3.10

$0.5x + 6.6y + S1 = 46.21$ 3.11

$6.6x + 0.5y + S2 = 65.323.12$

Table 5: Matlab code for impact of integrating renewable energy sources for rural electrification optimization using an intelligent agent

No of iterations	Basic	Z	X	y Sol	S1	S2
iter 1	Z	1	- 73.11	-62.22 0	0	0
	S1	0	0.5	6.6 46.21	1	0
S2 leaves x enters	S2	0	6.6	0.5 65.32	0	1
Iter 2	Z	1	0	-0.66	0	11 724
S1 Leaves while Y inters	S1	0	0	6.56	0 41.26	0.075
Pivot row	X	0	1	0.76	0	0.159.9
Iter 3	Z	1	0	0	0 10.99728.15	
Pivot	Y	0	0	1	00.01146.29	
	X					

The results obtained in the optimization are Solar and wind denoted by X is 9.4206 and the grid y is 6.2878

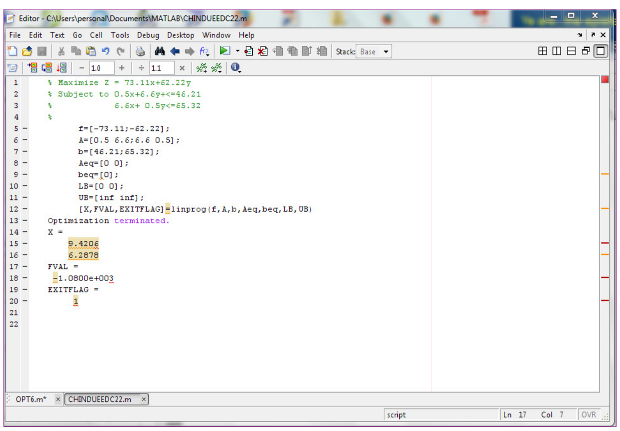

FIG 2: MATLAB PROGRAM to design an optimized intelligent agent for an effective power stability

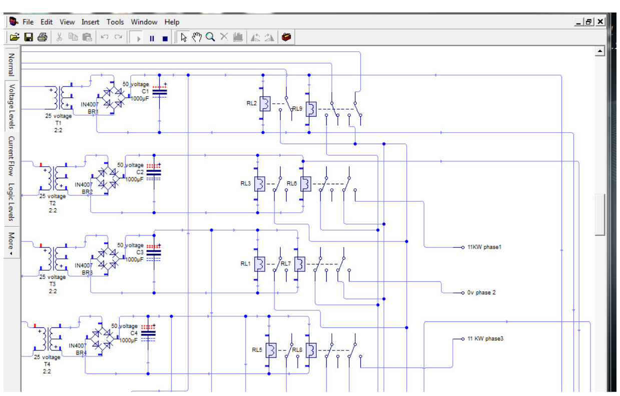

Fig 3 Automatic Transfer Switch (Ats)

In Fig 3 the incoming 11kV from the mains, wind, solar and battery were fed into the ATS with the help of the voltage comparator in the ATS. The ATS will pick the highest voltage signal from the solar, wind and mains to the inverter and it will continue to alternate at random stage depending on the voltage difference (from wind, solar and mains). The mode of transmission or transfer of voltage is very efficient because of the mode of switching which is Triac. Then the ATS comprises of a voltage comparator built around CD4047 which has the ability to detect a low and high signal that is one logic per second. The ATS has a display unit that indicates the current source in use as its rating (whether solar main, wind or battery).

III. RESULTS AND ANALYSIS

Table6 Conventional power stability in optimization of a micro grid operation under uncertainty.

Time	Conventional grid and renewable energy stability
1	0.3
2	0.3
3	0.3
4	0.3
5	0.4
6	0.4
7	0.4
8	0.4
9	0.4
10	0.3
11	0.3
12	0.3

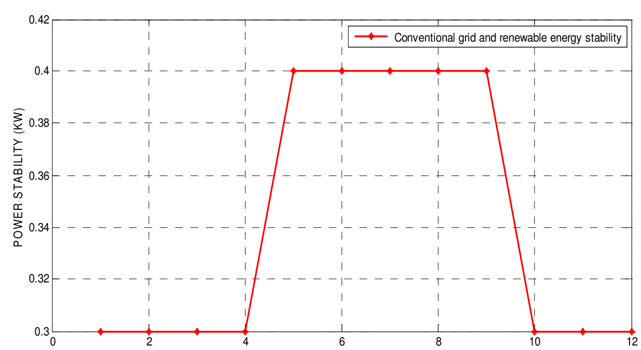

Fig 4 Conventional power stability in optimization of a micro grid operation under uncertainty.

Fig4. shows conventional power stability in optimization of a micro grid operation under uncertainty. The stability of optimization of a micro grid operation occurred at stability and time operation coordinates of (0.4, 4) through (0.4, 9). Within these coordinates there is stable power supply in a conventional approach.

Table 7 Power system stability in optimization of a micro grid operation under uncertainty using fuzzy.

Time	Grid and renewable energy stability using FUZZY controller
1	0.8321
2	0.8321
3	0.8321
4	0.8321
5	1.1090
6	1.1090
7	1.1090
8	1.1090
9	1.1090
10	0.8321
11	0.8321
12	0.8321

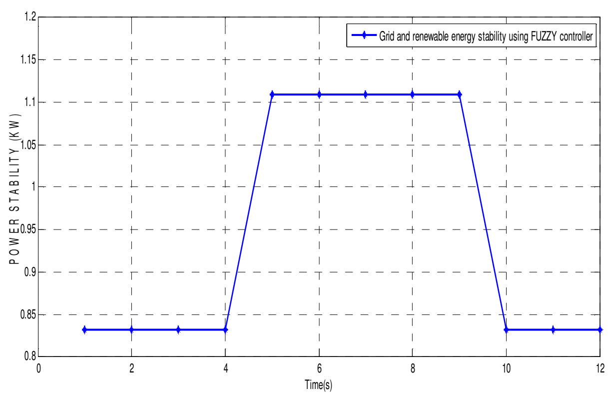

Fig 5: Power system stability in optimization of a micro grid operation under uncertainty using fuzzy.

Fig 5 shows power system stability in optimization of a micro grid operation under uncertainty using fuzzy controller. The stability of optimization of a micro grid operation occurred at stability and time operation coordinates of (1.109, 5) through (1.109, 9). Within these coordinates, there is stable power supply in optimization of a micro grid operation under uncertainty using fuzzy controller. The stability of power in optimization of a micro grid operation under uncertainty using fuzzy controller is higher than the conventional method.

Table 8: Power system stability in optimization of a micro grid operation under uncertainty using ANN

Time	Grid and renewable energy stability using ANN controller
1	0.8703
2	0.8703
3	0.8703
4	0.8703
5	1.1600
6	1.1600
7	1.1600
8	1.1600
9	1.1600
10	0.8703
11	0.8703
12	0.8703

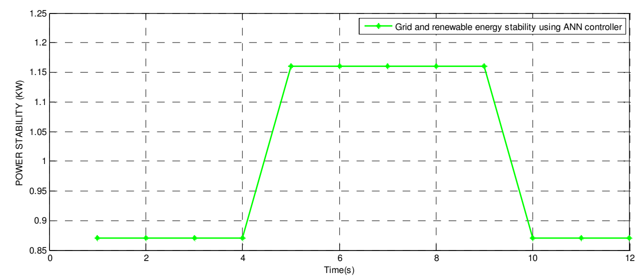

Fig 6: Power system stability in optimization of a micro grid operation under uncertainty using ANN controller.

Fig 6 shows power system stability in optimization of a micro grid operation under uncertainty using ANN controller. The stability of optimization of a micro grid operation occurred at stability and time operation coordinates of (1.16, 5) through (1.16, 9). In these coordinates there is stable power supply in optimization of a micro grid operation under uncertainty using ANN controller. The stability of power in optimization of a micro grid operation under uncertainty using ANN controller is higher than either the conventional method or using fuzzy controller.

Table 9 power system stability in optimization of a micro grid operation under uncertainty using model predictive control (MPC)

Time	Grid and renewable energy stability using MPC
1	0.9172
2	0.9172
3	0.9172
4	0.9172
5	1.2230
6	1.2230
7	1.2230
8	1.2230
9	1.2230
10	0.9172
11	0.9172
12	0.9172

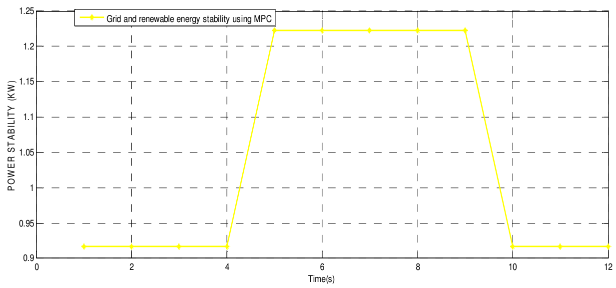

Fig 7 power system stability in optimization of a micro grid operation under uncertainty using model predictive control (MPC).

Fig 7 shows power system stability in optimization of a micro grid operation under uncertainty using model predictive controller. The stability of optimization of a micro grid operation occurred at stability and time operation coordinates of (1.223, 5) through (1.223, 9). In these coordinates there is stable power supply in optimization of a micro grid operation under uncertainty using MPC. The stability of power in optimization of a micro grid operation under uncertainty using MPC controller is highest among the other three the conventional method. Using fuzzy controller and using ANN.

Table 4.5 Comparing power system stability in optimization of a micro grid operation under uncertainty using conventional, fuzzy, ANN and model predictive control (MPC)

Time	Conventional grid and renewable energy stability	Grid and renewable energy stability using FUZZY controller	Grid and renewable energy stability using ANN controller	Grid and renewable energy stability using MPC
1	0.3	0.8321	0.8703	0.9172
2	0.3	0.8321	0.8703	0.9172
3	0.3	0.8321	0.8703	0.9172
4	0.3	0.8321	0.8703	0.9172
5	0.4	1.1090	1.1600	1.2230
6	0.4	1.1090	1.1600	1.2230
7	0.4	1.1090	1.1600	1.2230
8	0.4	1.1090	1.1600	1.2230
9	0.4	1.1090	1.1600	1.2230
10	0.3	0.8321	0.8703	0.9172
11	0.3	0.8321	0.8703	0.9172
12	0.3	0.8321	0.8703	0.9172

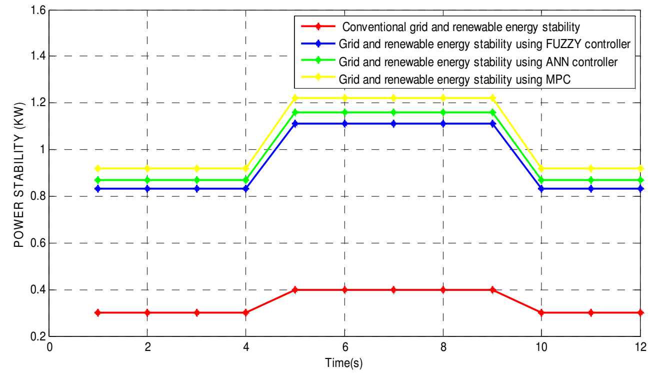

Fig 8 Comparing power system stability in optimization of a micro grid operation under uncertainty using conventional, fuzzy, ANN and Model predictive control (MPC)

In fig 8 the stability of conventional approach occurred at coordinates (0.4, 5) through (0.4, 9), while that of using fuzzy controller occurred at coordinates of (1.109,5) through (1.109, 9). When using Artificial Neural Network (ANN) controller, power stabilities occurred at coordinates (1.16, 5) through (1.16, 9) and that when MPC is used stability occurred at coordinates (1.223, 5) through (1.223, 9).

With these results it shows that in optimization of a micro grid operation under uncertainty using model predictive control (MPC) gives the highest power system stability when compared among the other three like conventional, fuzzy and ANN.

IV. CONCLUSIONAND RECOMMENDATION

Conclusion

Instability in power supply in our society and the country at large has led to liquidation of many establishments that solely depend on power for their daily activities. This instability in power supply observed in the country can be overcome by optimization of a micro grid operation under uncertainty using Model Predictive Control. This can be done in this manner, characterizing the micro grid operation, determining the threats in micro grid operation, designing a model predictive controller rule base that will eradicate the threats in micro grid operation thereby enhancing its operation, training ANN in this rule base for effective eradication of its operational threats thereby enhancing its operational efficiency, designing a Simulink model for optimization of a micro grid operation under uncertainty using model predictive control and validating and justifying the operational efficiency of a micro grid with and without MPC.

Contribution to knowledge

This research demonstrates the effectiveness of MPC in Microgrid operation optimization. The Simulink design of optimization of a micro grid operation under uncertainty using model predictive control was designed in MATLAB environment to enable engineer in the field to operate.

Recommendations

In near future, an incorporation of model predictive control to enhance stable power supply in our power utility companies is encouraged

ACKNOWLEDGMENT

I would like to thank my family for their continued support throughout especially at difficult times; my parents for the motivation to pursue more knowledge and higher educational qualification, my darling wife Damilola for her patience and understanding for the duration of the programme, my siblings Osaze and Itohan for their words of advice and encouragement

I sincerely wish to express profound gratitude to all those who contributed one way or the other towards this research work and making it a reality especially to my supervisor; Prof. I.I. Eneh for his guidance through the programme. Also my HOD, Dr. Mrs D.O.Abonyi, the project coordinator for the programme, Dr EnePrincewill, mycourse lecturers;Professors Greg Onoh&James Eke, and Dr Alor, and all the lecturers in the department I thank you all for your care, advice and all round guidance.

I also acknowledge the invaluable work of my Class Rep, Nwabueze Charles Nnaemeka, and those who stood for the growth of the Electrical and Electronic Engineering Department. Not to forget my colleagues in the office for their assistance in covering my shifts to allow me travel to school.

Thanks to you all.
God bless you.

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MATLAB SIMULATION CODE

```
A = [ 1 2 3 4 5 6 7 8 9 10 11 12];
B = [0.3 0.3 0.3 0.3 0.4 0.4 0.4 0.4 0.4 0.3 0.3 0.3];
plot(A,B,'-Or','MarkerFaceColor','r','MarkerSize',12,'Linewidth',3);

grid on
Ylabel(' Energy stability ');Xlabel('Time(s)')
Legend('Conventional grid and renewable energy stability ')

A = [ 1 2 3 4 5 6 7 8 9 10 11 12];
B = [0.8321 0.8321 0.8321 0.8321 1.109 1.109 1.109 1.109 1.109 0.8321 0.8321 0.8321];
plot(A,B,'-Ob','MarkerFaceColor','b','MarkerSize',12,'Linewidth',3);

grid on
Ylabel(' Energy stability ');Xlabel('Time(s)')
Legend('Grid and renewable energy stability using FUZZY controller ')

A = [ 1 2 3 4 5 6 7 8 9 10 11 12];
B = [0.3 0.3 0.3 0.3 0.4 0.4 0.4 0.4 0.4 0.3 0.3 0.3];
C = [0.8321 0.8321 0.8321 0.8321 1.109 1.109 1.109 1.109 1.109 0.8321 0.8321 0.8321];
D = [0.8703 0.8703 0.8703 0.8703 1.16 1.16 1.16 1.16 1.16 0.8703 0.8703 0.8703];
E = [0.9172 0.9172 0.9172 0.9172 1.223 1.223 1.223 1.223 1.223 0.9172 0.9172 0.9172];

plot(A,B,'-Sr','MarkerFaceColor','r','MarkerSize',12,'Linewidth',3);
hold on
plot(A,C,'-Pb','MarkerFaceColor','b','MarkerSize',12,'Linewidth',3);
hold on
plot(A,D,'-Pg','MarkerFaceColor','g','MarkerSize',12,'Linewidth',3);
hold on
plot(A,E,'-Py','MarkerFaceColor','y','MarkerSize',12,'Linewidth',3);

grid on
Ylabel(' renewable energy stability ');Xlabel('Time(s)')
Legend('Conventional grid and renewable energy stability)','Grid and renewable energy stability using FUZZY controller ','Grid and renewable energy stability using ANN controller','Grid and renewable energy stability using MPC')
```

Optimization code