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# A Model Predictive Control Approach for Efficient Optimization of Microgrid Operations using Mixed Integer Linear Programming

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***Abstract*— Microgrid is a subsystem comprises of distributed generator (DG) s, non-conventional generators, storage devices and controllable loads. Microgrids are one of the centers for penetration of non-conventional energy resources, storage backup and management of distribution generation units. It results reduction in costs, emission gases, transmission & distribution losses and also conventional energy crisis. Simply it is highly reliable and ecofriendly. In this paper, we present a study of Model Predictive control (MPC) Approach using mixed integer linear programming (MILP) technique while satisfying operational constraints and a time varying requests. MILP technique is used to formulate the Overall optimization problem and commercial solvers are used for substantial improvements in solution quality and computational burden. To assess the performance of the online optimization-based control strategy a microgrid case study is employed and the simulation results are discussed. A modification for above case study was done by considering uncertainties of non-conventional energy. During uncertainties to meet the critical load demand, DG Units are increased. The results show the effectiveness and feasibility of the proposed approach.**

***Index Terms*— Microgrids, Conventional Energy, Non-Conventional Energy, Distributed Generators, Model Predictive Control (MPC), Mixed Integer Linear Programming (MILP), Commercial solvers, optimization.***

NOMENCLATURE

| | |
|---|---|
| DG | : Distributed Generation |
| PCC | : Point of Common Coupling |
| DER | : Distributed Energy Resource |
| PV | : Photovoltaic |
| WT | : Wind Turbine |
| KW | : Kilowatt |
| DSM | : Demand Side Management |
| ISO | : Independent System Operator |
| MPC | : Model Predictive Control |
| MIP | : Mixed Integer Problem |
| MILP | : Mixed Integer Linear Programming |

## I.INTRODUCTION

Countries with abundant electrical energy became developed countries. In developing countries also electrical energy become a key role to achieve their targets, the reason behind this is in three sectors i.e. primary sector, Industrial and tertiary sector electrical energy playing vital role. With is there is bulk power generation, transmission, distribution and utilization. In this process one side depletion of conventional energy resources and the other side transmission losses and distribution losses. To balance the power generation and energy demand, reduction of losses has to takes place. In this there are three major problems 1) Day-by-day resources are depleting; 2) there is growth in energy demand and 3) Transmission and distribution losses are high.

High penetration of non-conventional energy resources, storage backup, distributed generation units and energy efficiency provides a sustainable way to meet the growing energy demand. New energy management systems also required for optimally managing the DG units, demand side policies and interacting with the utility grid. Approach for designing a new energy management system for DG unit is 1) considering the subsystems of the utility grid; 2) building a model of the subsystem which is as simple as possible; 3) formulate a feasible operation optimization and 4) deal with uncertainty. The two promising models for these energy systems are microgrids and energy hubs.

Microgrid is one of the solutions for reduction of prices, emission gases and also energy crisis. Simply it is highly reliable and reduced emissions. It is an energy management system comprises of Distributed generators, non-conventional energy generator units, storage units, critical and controllable loads, which can be operate in parallel with grid or in an island mode, see [1] and [2]. Microgrids have ability to manage and coordinate DG units, storages and loads in decentralized way and it helps to reduce the Centralized management and coordination [3]. As management and arrangement of Microgrid units is cost effective, efficient optimization of microgrid operations are required and also to efficiently manage its energy resources [2], [4].

Storage modelling is required to coordinate storage use with non-conventional energy generation, energy prices and complexity of the charging/ discharging schedule [5] but no current modelling tools energy storage model and controllable loads in a smart power grid environment [6].

Notice further that overall optimization problem includes storage modelling, power exchange with the utility grid and the demand side policies for controllable loads like demand side management (DSM). Moreover microgrid modelling constitutes two types of decision variables i.e. continuous variables (storage charging/discharging rates) and discrete (ON/OFF states of DGs and controlled loads) and the problem gives no exact solution for mixed integer nonlinear technique, which is generally used for the formulation see [7]-[9]. Coping up with uncertainties in non-conventional energy resources, energy demand and prices further complicates the microgrid coordination and management.

Several independent system operators (ISOs) and regional transmission organizations are run by using mixed integer problem (MIP) algorithms. Computational advances and modeling capabilities of MIP algorithms gives better solution for real-time market and day-ahead problems [10]. Exclusion of unit commitment problems to the optimality causes several issues [11]. Therefore, a microgrid operation optimization problem requires feasible formulation which includes the particular key features of a microgrid.

In this paper, we tackle the operation optimization problem of a microgrid. This aims at minimization of overall operating costs of the system to meet the predicted load demand of a certain period typically one day i.e. 24 hour horizon while satisfying operational constraints.

*A. Literature Survey*

Microgrid has complexity in operation optimization problem, optimization algorithms and appropriate modeling frameworks gives large economic benefits from its improved solution. Power dispatch problem for microgrids can be solved by metaheuristics and heuristics such as genetic algorithms [12], tabu search algorithms and evolutionary strategies [13].

From studies microgrids can achieve high performance through: 1) prediction based advanced control algorithms accounting for system uncertainty; 2) Deployment of demand side policies; 3) compensation of physical imbalances with the optimal usage of storage devices; and 4) applying optimal based approaches gives better solution than heuristic based approaches (see [14]-[17]). The proposed approaches may not be suitable for real-time applications as those are computationally intensive and can produce suboptimal solutions (see [17]-[19]). Further, the optimal problem may stays nonlinear or features such as minimum up time, down time and demand side policies may neglected. To get the feasible solution, the microgrid optimization problem may solve as several MINLPs such as one separate problem for storage management, one for unit commitment and so on [20].

Recently several factors in the power system community have led usage model predictive control (MPC) approach [21]: 1) it is based on predictions and future behaviour of the system i.e. demands forecasts; 2) feedback mechanism makes the system robust against uncertainty. 3) It can handle system constraints. MPC method gives better results for unit commitment problem with wind generation [22]. During island mode of operation, for reactive power control, MPC-based dynamic voltage and var control scheme has developed [23]. MPC approach is used for optimal dispatch in power system especially to describe hybrid systems continuous/discrete dynamics and switching at different operating conditions [24]. Without considering storage modelling, demand side polices and ON/OFF conditions of generation units, MPC algorithm is proposed to solve economic dispatch problem with large intermittent sources [25].

[26] and [27] propose an MPC algorithm to manage the energy flows of microcombined heat and power unit inside a household system. In addition, the household can sell/purchase electrical energy to/from the utility grid and heat and electrical energy can be stored in specific storage devices. In [28] and [29], an MPC framework is applied to minimize the generating cost of a certain period. Demand has to meet using power dispatch subject to limits on power generation and ramp rates. A supervisory control system which includes MPC is designed to compute the power references of wind/solar energy generation subsystem at each sampling time, minimizing cost function. These power references are sent to local controllers to drive the subsystems at requested power references [30]. In [31], two distributed supervisory MPC controllers are applied instead of the centralized supervisory MPC controller, to the local controller, optimal reference trajectories are provided. For this start-up/shut down are not addressed and the problem is nonconvex and nonlinear.

For an islanded microgrid, which comprises PV panels, two WTs, a DG unit and an energy storage system, rolling horizon strategy has proposed based on an energy management system [32]. The optimization problem includes nonlinear constraints (DG unit and storage device) and are approximated by piece-wise linear models. MILP technique is used to solve the problem and to yield suboptimal solutions.

*B. Assumptions*

In a microgrid control structure, different control approaches and time scales should be addressed: 1) individual components phase, frequency and voltage electrical control can be done fast within seconds or less. 2) Economic dispatch and unit commitment of all DG units, non-conventional energy units, storage devices, load forecasting, demand side policies and energy exchange with the utility grid on time scales of hours. Thus a hierarchical control structure is a reasonable approach to develop two controllers i.e. high level controller is a centralized and it is on the top of the hierarchy and the second level consists Distributed Energy Resources (DER) and load controllers [33]. The main aim of the centralized algorithm is to economically optimize power dispatch by generate suitable set points for all sources and storages and to meet the given demand. The task of the local controllers is to guarantee that the system tracks the power reference values.

*C. Main Contributions*

In [34] and [35], for a microgrid, a control oriented approach, a high level optimization and use of MPC in combination with MILP is presented. Based on the predictions of future behaviour of the system, non-conventional energy production and demand forecasts, microgrid operations are decided. We utilized the mixed logical dynamical framework and the approach described in [36]. To state the problem formulation, we assume DG units fuel consumption and emission functions.

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In our approach, without resorting to decomposition techniques or heuristics, by considering solvers an optimization problem is developed by including as many details as possible and also we modelled the DG units physical and technical features by considering low number of constraints and variables.

Further, An MPC approach is considered which is a feedback mechanism used to compensate the uncertainties such as non-conventional power outputs, the time-varying load and energy prices for microgrid operations. Shorter sampling time is used to compute more and effective solutions to reach optimum.

In summary, microgrid modelling requires both continuous and discrete decision variables which results operation optimization problem is very difficult to solve. Providing a microgrid model adopting a formalized modelling approach i.e. mixed integer linear programming technique and it can be solved efficiently by cplex solver and the problem formulation is suitable for online control scheme e.g., Model Predictive Control approach.

Problem formulation has to be pointed out that, at the lower control level; voltage stability, power quality and frequency are assumed to be controlled automatically. Thus, the microgrid optimal operation planning problem minimizes overall operating costs subject to storage dynamics (charging/discharging mode), power balance, energy import/export from/to the utility grid and operational and capacity constraints.

This paper is further organized as follows: 1) Microgrid System Description, Modeling and Constraints in Section II; 2) Optimization Problem in Section III; 3) Simulation setup is discussed in Sections IV; 4) Simulation results are discussed in Section V; 5) finally conclusions are drawn.

*D. Terminology*

Formulation of the problem includes parameters, forecasts and the decision variables which are described in Tables I-III, respectively and for simplicity subscript   is omitted which is used to refer the   th unit. Moreover, vectors and matrices are denoted in bold. In this fuel consumption cost for a DG unit is assumed as quadratic function form.

$$C^{DG}(P) = a_1 P^2 + a_2 P + a_3$$

Table I: Parameters

| Parameters | Description |
|---|---|
| $N_g, N_l, N_c$ | Number of DG units, critical and controllable loads |
| $C^{DG}(P)$ | Fuel consumption cost of a DG unit depends on generated power |
| $a_1, a_2, a_3$ | Cost coefficients of $C^{DG}$ and its units [€/(kwh)$^2$,€/kwh, €] |
| $OM$ | Operating and maintenance cost of a DG unit [€/h] |
| $OM^b$ | Operating and maintenance cost of a storage unit [€/KWh] |
| $R_{max}$ | Ramp up limit of a DG unit [KW/h] |
| $T^{up}, T^{down}$ | Minimum up and down time of a DG unit [time-units] |
| $x^{sb}$ | constant stored energy loss in the sampling interval [KWh] |
| $x^b_{min}, x^b_{max}$ | minimum and maximum energy level of the storage unit [KWh] |
| $C^b$ | power limit of storage output [KW] |
| $T^g$ | maximum interconnection power flow limit at the PCC [KW] |
| $P_{min}, P_{max}$ | minimum and maximum power level of a DG unit [KW] |
| $\eta^c, \eta^d$ | charging and discharging efficiencies of storage unit |
| $\beta_{min}, \beta_{max}$ | minimum and maximum allowed curtailment of a controlled load |
| $C^{SU}, C^{SD}$ | start-up and shut-down costs of a DG unit [€] |
| $D^c$ | preferred power level of a controllable load [KW] |
| $\rho_c$ | curtailment's penalty weight |

Table II: Forecasts

| Forecasts | Description |
|---|---|
| $P^{res}$ | Sum of power production from non-conventional energy sources(RES) [KW] |
| $D$ | Power level required from a critical load [KW] |
| $C^P, C^S$ | Purchasing and selling energy prices [€/KWh] |

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Table III: Logical and Decision Variables

| Variables | Description |
|---|---|
| $\delta$ | Off(0)/on(1) state of a DG unit |
| $\delta^b$ | Discharge(0)/charge(1) of the storage unit |
| $\delta^g$ | Export(0)/import(1) to/from the utility grid |
| $P$ | Power level of a DG unit [KW] |
| $P^b$ | Power exchanged (+ve for charging) with the storage unit [KW] |
| $P^g$ | power level of the utility grid, for Importing(+ve)/exporting(-ve) [KW] |
| $x^b$ | Stored energy level [KWh] |
| $\beta$ | Percentage of curtailed power |

## II.MICROGRID SYSTEM DESCRIPTION MODELLING AND CONSTRAINTS

To minimize operating costs with feasible and suitable real-time computation of the microgrid system, a brief description of key features and modeling setup of this subsystem is described.

Here, we consider a discrete time model of a storage unit constitutes $x^b$ the stored energy level at time $k$ (divided by $\Delta T$) and $P^b(k)$ the power exchanged with the storage unit as follows:

$$x^b(k+1) = x^b(k) + \eta P^b(k) - x^{sb} \tag{1}$$

where

$$\eta = \begin{cases} \eta^c, & \text{if} P^b(k) > 0 \text{ (charging mode)} \\ 1/\eta^d, & \text{otherwise (discharging mode)} \end{cases} \tag{2}$$

with

$$0 < \eta^c, \eta^d < 1.$$

Losses are represented by charging and discharging efficiencies and $x^{sb}$ represents constant stored energy loss in the sampling time. $P^b(k)$, the power level of the storage unit at time $k$, is greater than zero then this will be charging mode of the storage unit and vice versa.

In [36], the standard approach is described. To model the logical condition and the storage dynamics a binary variable $\delta^b(k)$and $z^b(k) = \delta^b(k)P^b(k)$, an auxiliary variable are introduced.

$$P^b(k) \geq 0 \Leftrightarrow \delta^b(k) = 1 \tag{3}$$

and

$$x^b(k+1) = \begin{cases} x^b(k) + \eta^c P^b(k) - x^{sb}, & \text{if } \delta^b(k) = 1 \\ x^b(k) + 1/\eta^d P^b(k) - x^{sb}, & \text{otherwise} \end{cases}$$

In this, logical conditions are expressed as mixed integer linear inequalities. The storage dynamics and its constraints are rewritten with the help of above mixed integer linear inequalities as follows:

$$x^b(k+1) = x^b(k) + (\eta^c - 1/\eta^d) z^b(k) + 1/\eta^d P^b(k) - x^{sb}$$

Subject to the constraint

$$\mathbf{E}_1^b \delta^b(k) + \mathbf{E}_2^b z^b(k) \leq \mathbf{E}_3^b P^b(k) + \mathbf{E}_4^b \tag{4}$$

where the column vectors $\mathbf{E}_1{}^b$, $\mathbf{E}_2{}^b$, $\mathbf{E}_3{}^b$ and $\mathbf{E}_4{}^b$ are derived by considering the if..then conditions described in (3), the six mixed integer linear inequalities modeling and the auxiliary variable which hides a nonlinearity is as follows:

$$z^b(k) = \delta^b(k) P^b(k) \tag{5}$$

On considering

$$m = -C^b,\ M = C^b, f(k) = P^b(k) \text{ and } \delta = \delta^b(k).$$

the logical condition is rewritten as follows (the interested reader is referred to [36] for the statement):

$$\begin{cases} C^b \delta^b(k) & \leq P^b(k) + C^b \\ -(C^b + \varepsilon)\delta^b(k) & \leq -P^b(k) - \varepsilon. \end{cases} \tag{6}$$

Here, the first two elements of the column vectors in (4) as follows:

$$\mathbf{E}_1^{b'} = [C^b \ -(C^b + \varepsilon) \ldots .]$$

$$\mathbf{E}_2^{b'} = [0 \quad 0 \ldots \ldots ..]$$

$$\mathbf{E}_3^{b'} = [1 \ \ -1 \ldots ..]$$

$$\mathbf{E}_4^{b'} = [C^b \ -\varepsilon \ldots .]$$

The other elements are obtained by imposing the inequalities to the variable $z^b(k)$, consider f(k) = $P^b(k)$ and $\delta = \delta^b(k)$.

$$\begin{cases} z^b(k) & \leq & C^b \delta^b(k) \\ z^b(k) & \geq & -C^b \delta^b(k) \\ z^b(k) & \leq & P^b(k) + (1 - \delta^b(k)) \\ z^b(k) & \geq & P^b(k) - (1 - \delta^b(k)) \end{cases}$$

At each time interval $k$, energy production and utilization should be balanced. Accordingly the power balance equation i.e. equality constraint is as follows:

$$P^b(k) = \sum_{i=1}^{N_g} P_i(k) + P^{res}(k) + P^g(k) - \sum_{j=1}^{N_l} D_j(k) - \sum_{h=1}^{N_c} [1 - \beta_h(k)] D_h^c(k). \tag{7}$$

Collection of all decision variables as vector $\mathbf{u}(k)$ and all known disturbances which will obtain from forecasts as vector $\mathbf{w}(k)$, Then, the $P^b(k)$ can be rewrite as follows:

$$P^b(k) = \mathbf{F}'(k)\mathbf{u}(k) + \mathbf{f}'\mathbf{w}(k) \quad (8)$$

where

$$\mathbf{u}(k) = [\boldsymbol{P}'(k) \;\; P^g(k) \;\; \boldsymbol{\beta}'(k) \;\; \boldsymbol{\delta}'(k)]' \in \mathbb{R}^{N_u} \times \{0,1\}$$

$$\mathbf{w}(k) = [P^{res}(k) \;\; \boldsymbol{D}'(k) \;\; \boldsymbol{D}^{c'}(k)]' \in \mathbb{R}^{N_w}$$

where

$N_u = N_g + 1 + N_c,\; N_w = 1 + N_l + N_c;$ all power levels, generators ON/OFF states, the critical demand, controllable loads power level and the curtailments are denoted by $\mathbf{P}(k)$, $\boldsymbol{\delta}(k)$, $\boldsymbol{D}(k)$, $\boldsymbol{D}^c(k)$and $\boldsymbol{\beta}(k)$, respectively. The vectors $\mathbf{F}'(k)$ and $\mathbf{f}'$ in (8) as follows:

$$\mathbf{F}'(k) = [\underbrace{1 \dots 1}_{N_g} \;\; 1 \;\; \underbrace{\dots D_i^c(k) \dots}_{N_c} \;\; \underbrace{0 \dots 0}_{N_g}]$$

$$\mathbf{f}' = [1 \;\; \underbrace{-1 \dots -1}_{N_l} \;\; \underbrace{-1 \dots -1}_{N_c}]$$

Thus, on substituting (8) in (4), the storage level can be expressed as follows:

$$x^b(k+1) = x^b(k) + (\eta^c - 1/\eta^d)z^b(k) + 1/\eta^d[\mathbf{F}'(k)\mathbf{u}(k) + \mathbf{f}'\mathbf{w}(k)] - x^{sb}. \quad (9)$$

*B. Interaction with the Utility Grid*

When microgrid is connected to grid, it can purchase and sell energy from/to the utility grid. On considering the same procedure outlined above, we introduce an auxiliary variable $C^g(k)$ and a binary variable $\delta^g(k)$ to model the possibility i.e. either to sell energy to or purchase energy from the utility grid. The logical condition is rewritten as follows:

$$P^g(k) \geq 0 \Leftrightarrow \delta^g(k) = 1$$

and

$$C^g(k) = \begin{cases} c^P(k)P^g(k), & \text{if } \delta^b(k) = 1 \\ c^S(k)P^g(k), & \text{otherwise} \end{cases}$$

We again express the mixed integer linear inequalities with the help of the if..then conditions. Then mixed integer linear inequalities are expressed to represent purchasing and selling behavior of the microgrid as follows:

$$\mathbf{E}_1^g\delta^b(k) + \mathbf{E}_2^g C^g(k) \leq \mathbf{E}_3^g(k)P^g(k) + \mathbf{E}_4^g. \quad (10)$$

where the column vectors $\mathbf{E}_1{}^g$, $\mathbf{E}_2{}^g$, $\mathbf{E}_3{}^g(k)$ and $\mathbf{E}_4{}^g$ are derived by considering logical condition ,the six modeling linear inequalities. The matrix $\mathbf{E}_3{}^g(k)$ is time-varying because of the time-varying energy prices. This all will be done only when microgrid is in grid-connected mode not in island mode.

Here, the first two elements of the column vectors in (10) as follows:

$$\mathrm{E}_1^{g'} = [T^g \;\; -(T^g + \varepsilon) \dots]$$

$$\mathrm{E}_2^{g'} = [0 \;\; 0 \dots \dots]$$

$$\mathrm{E}_3^{g'}(k) = [1 \;\; -1 \dots]$$

$$\mathrm{E}_4^{g'} = [T^g \;\; -\varepsilon \dots]$$

*C.Loads*

In this paper, we consider two types of loads:

1) Critical loads, the loads which are always requires non-stop power supply i.e. it to met its corresponding power level demand.

2) Controllable loads, the loads which can be shed or reduced during emergency situations i.e. day-time lighting and standby devices and supply constraints for which demand side policies can be applicable.

In demand side programs, level of curtailment of controllable loads are specified by customers only. It is so helpful during island mode of microgrid operation since microgrid is necessary to work completely by its own. Hence, to reduce controllable loads demand level, its magnitude should be flexible with a preferred level. For load curtailment/shedding, certain cost is associated i.e. penalty for the users who will face discomfort for this. In this a continuous-valued variable $0 \leq \beta_c(k) \leq 1$ is defined to associate at each controllable load c and sampling time To make the microgrid operations feasible a preferred power level percentage to be curtailed at the time interval $k$ is represents by above variable. If curtailment is not allowed at a certain time interval an equality constraint can be set, $\beta_c(\hat{k}) = 0.$

*D. Generator Operating Conditions*

To keep controllable generation unit ON/OFF (minimum up/down times) on the minimum amount of time at each sampling time $k$, without resorting to any additional variable the operating constraints can be expressed by the mixed integer linear inequalities as follows:

$$\delta_i(k) - \delta_i(k-1) \leq \delta_i(\tau), \qquad \text{(OFF/ON switch)}$$

$$\delta_i(k-1) - \delta_i(k) \leq 1 - \delta_i(\tau), \qquad \text{(ON/OFF switch)} \quad (11)$$

where $i = 1, \dots, N_g,$ if we consider the constraints on the minimum up time $\tau = k+1, \dots, \min(k + T_i^{up} - 1, T)$ otherwise $\tau = k+1, \dots, \min(k + T_i^{down} - 1, T)$.

For instance consider the $i$ th unit at time step $\hat{k}$, with $\delta_i(\hat{k} - 1) = 0,$ i.e. the unit was OFF during the previous sampling period. The first $T_i^{up} - 1$ constraints in (11) will

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force all the binary optimization variables corresponding to the unit ON-/OFF-state to be equal to 1 when the value is assigned to the optimization variable $\delta_i(\hat{k})$, for the next $T_i^{up} - 1$ sampling times.

$$\delta_i(\hat{k}) - \delta_i(\hat{k}-1) \le \delta_i(\hat{k}+1)$$

$$\delta_i(\hat{k}) - \delta_i(\hat{k}-1) \le \delta_i(\hat{k}+2) \qquad (12)$$

To satisfy the constraints $T_i^{up} = 3$ forces the right-hand side of the inequalities (12) to be equal to 1.

Two auxiliary variables $SU_i(k)$ *and* $SD_i(k)$ are introduced for modeling the DG unit startup and shutdown costs, for the *i* th DG generation unit at time *k*, respectively. These auxiliary variables must satisfy the mixed integer linear constraints as follows:

$$SU_i(k) \ge c_i^{SU}(k)[\,\delta_i(k) - \delta_i(k-1)]$$

$$SD_i(k) \ge c_i^{SD}(k)[\,\delta_i(k-1) - \delta_i(k)]$$

$$SU_i(k) \ge 0$$

$$SD_i(k) \ge 0 \qquad (13)$$

where $i = 1, \dots, N_g$ (see [38]).

## III.OPTIMIZATION PROBLEM

To cover the microgrid demand, minimize the generators running costs and imported electricity costs from the utility grid in the sampling interval or day, the microgris optimal operational planning takes decisions on generators internal production optimal scheduling, storage and controllable loads. The microgrid controller must take high level decisions at every time step as follows:

- Unit commitment (UC) i.e. when should a generation unit be start and stop;
- Economic Dispatch (ED) i.e. at minimum cost, how much each generation unit should meet this load;
- Storage operations i.e. charging and discharging optimal scheduling;
- Demand side policies i.e curtailment options, to when the controllable loads have shed/curtailed;
- In grid-connected mode, when and how much energy should be sold and purchased to/from the utility grid;
- how much energy has to be stored.

To generate an optimal plan, the objective function can be formulated as a MILP optimization problem by using modeling of section II. The model will be imperfect when the plan is subject to uncertainty and the system state will not evolve as predicted. Moreover, the single MILP is an open loop solution which does not account for these uncertainties. Embedding MILP optimizations within an MPC framework is a possible remedy so that the uncertainty can be potentially compensated by implementing a feedback control law. Two solutions coincide when the uncertainty is not present. To formulate the MPC problem, cost function formulated by MILP has to define.

### *A. Mixed Integer Linear Programming*

It is a mathematical feasible or optimal program in which few or whole variables are restricted to be integers. In this, the objective function and the constraints (other than the integer constraints) are linear. In a microgrid system, continuous and discrete-valued dynamics are interacting. One side the physical quantities such as energy and power flows are represented by continuous variables and the other side DG units ON/OFF status, the storage charging/discharging state and the minimum up and down time constraints are represented by discrete variables by using binary values. In addition, the behavior of a microgrid system and its components can be described by both difference and differential equations e.g., logical statements, i.e. statements of the form if..then.. else and storage dynamics. As we are interested in model predictive control, a prediction model of the system has to construct. In [36], casting a logical statement of a given form into linear mixed integer constraints has shown i.e. constraints involving continuous and discrete- valued variables which were already described in section II.

$$f(k) \ge 0 \Leftrightarrow \delta = 1$$

$$\text{is true if and only if} \begin{cases} -m\delta & \le \quad f(k) - m \\ -(M+\varepsilon)\delta & \le \quad -f(k) - \varepsilon \end{cases}$$

similarly

$$y = \delta f(k) \;\; \text{is equivalent to} \begin{cases} y \le M\delta \\ y \ge m\delta \\ y \le f(k) - m(1-\delta) \\ y \ge f(k) - M(1-\delta) \end{cases}$$

where f is a function upper and lower bounded by *M* and *m*, δ is a binary variable, *y* is a real variable, ε is a small tolerance i.e. typically the machine precision respectively. As MILP solving algorithms only handle nonstrict inequalities, the tolerance ε is needed to transform a constraint of the form $y < 0$ into $y \le 0$.

### *B. Fuel Consumption Cost Function*

There is a requirement to linear approximate the cost function's fuel consumption. Compare to quadratic programs, mixed integer linear programs are computationally more efficient [39]. Without introducing binary variables, the DG generator fuel cost function $C^{DG}(P) = a_1P^2 + a_2P + a_3$ is approximated as maximum of affine functions [40].

$$C^{DG}(P) \approx \left\{ \max_{j=1,\dots,n} \{S_jP + s_j\} \right\} = \|SP + s\|_\infty \qquad (14)$$

Where *P* represents generated power; $S_j$ and $s_j$ respectively; are obtained by linearizing the function at *n* points and *j* extracts the *j* th row of *S* and *s*.

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*C. Cost Function*

The microgrid optimal operational planning can be achieved by minimization overall operating costs. The following function includes production, startup & shutdown costs decisions, along with possible curtailment penalties and earnings:

$$\sum_{k=0}^{T-1}\sum_{i=1}^{N_g}[C_i^{DG}(P_i(k)) + OM_i\delta_i(k) + SU_i(k) + SD_i(k)] + OM^b[2z^b(k) - P^b(k)] + C^g(k) + \rho_c \sum_{h=1}^{N_c} \beta_h(k) D_h^c(k) \quad (15)$$

where $k$ and $T$ represents instantaneous time and length of the prediction horizon 24 hour. $2z^b(k) - P^b(k)$ models the storage unit power exchange using (5) and (8). The term $OM_iP_i(k)$ represents operative and maintenance costs of the *i* th DG unit that depend on the generated power. Moreover, the term $OM^b[2z^b(k) - P^b(k)]$ reduces the charging and discharging frequency and $C^g(k)$ can be negative when energy is sold to the utility grid.

We introduced the auxiliary variable $\sigma_i(k)$ to write the cost function in compact form, at each time *k* to approximate the *i* th DG unit generating costs and the vector $\mathbf{z}(k)$ collects all the auxiliary variables as follows:

$$\mathbf{z}(k) = [\sigma'(k)\ \ C^g(k)\ \ SU'(k)\ \ SD'(k)\ \ z^b(k)]' \in \mathbb{R}^{3N_g+}$$

where $\sigma_i(k)$, the generators start-up and shutdown costs are denoted by, $\sigma(k)$, $SU(k)$ and $SD(k)$ respectively. The input sequence is denoted by $\mathbf{u}_k^{T-1}$ where $\mathbf{u}(k)$ is introduced in (8), at each time *k*, we designed it as $\mathbf{u}_k^{T-1} = (\mathbf{u}(k), \ldots\ldots, \mathbf{u}(k+T-1))$. then the cost function is rewritten as follows:

$$\sum_{k=0}^{T-1} \mathbf{c}_u'(k)\mathbf{u}(k) - OM^b\mathbf{F}'(k)\mathbf{u}(k) - OM^b\mathbf{f}'\mathbf{w}(k) + \mathbf{c}_z'\mathbf{z}(k)$$

where the column vectors $\mathbf{c_u}$ and $\mathbf{c_z}$ are given below and the term $-OM^bP^b(k)$ in (15), where $P^b(k)$ is given in (8) is used to derive the term $-OM^b\mathbf{F}'(k)\mathbf{u}(k) - OM^b\mathbf{f}'\mathbf{w}(k)$.

$$\mathbf{c}_z' = [\underbrace{1 \ldots 1}_{N_g}\ \ 1\ \ \underbrace{1 \ldots 1}_{2.N_g}\ \ 2.OM^b]$$

$$\mathbf{c_u}(k)' = [\underbrace{0 \ldots 0}_{N_g}\ \ 1\ \ \underbrace{\ldots \rho_i(k) D_i^c(k) \ldots}_{N_c}\ \ \underbrace{\ldots OM_i \ldots}_{N_g}].$$

*D. Capacity and Terminal Constraints*

Additional constraints such as capacity and terminal constraints have to be met to pose the final MILP optimization problem.

$$x_{\min}^b \le x^b(k) \le x_{\max}^b \quad (16a)$$

$$P_{i,\min}\delta_i(k) \le P_i(k) \le P_{i,\max}\delta_i(k) \quad (16b)$$

$$|P_i(k+1) - P_i(k)| \le R_{i,\max}\delta_i(k) \quad (16c)$$

$$\beta_{h,\min} \le \beta_h(k) \le \beta_{h,\max} \quad (16d)$$

Where $i = 1, \ldots, N_g$ *and* $h = 1, \ldots, N_c$. the above constraints are physical bounds on the storage device in (16a); DG units power flow limits in (16b) and their ramp up and ramp down rates in (16c); and curtailment bounds of the controllable loads in (16d). Note that if the power generated $P_i(k)$ from the $i$ th DG unit at time *k* is positive, then the binary variable $\delta_i(k)$ will be 1 otherwise 0. The binary variable $\delta_i(k)$ can be avoid in the inequality (16b) when $P_{i,\min}$ is very small positive value.

*E. Model Predictive Control Problem*

In this section, we incorporate feedback and predictions into control action on the basis of optimization problem. For this we consider model predictive control approach, a model of the controller is used to predict the future evolution of the controller to optimize the control signal. Based on this we formulate the optimization problem in some given criteria and the solution yields a trajectory of inputs and states into the future which satisfy the dynamics and constraints of the microgrid operations. At each time *k*, optimal control problem can solve over a finite future horizon usually for the 24 h based on predictions of the non-conventional energy production, upcoming demand and energy prices. We implement only first optimal move or the input sequence and subsequently the horizon is shifted i.e. at time *k* +1, repeat the optimization and so on. By this the new state of the system will get new measurements and by using this new information a new optimization problem is solved. The new optimal plan can potentially compensate with this receding horizon approach, for any disturbance acted on the system. We denote $x^b(k+j|k)$, with $j > 0$, to present the MPC policy, at time step *k* + *j* predicted at time *k* the storage model in (9).

The MPC scheme computes the optimal control sequence $\mathbf{u}_k^{T-1}$ at each time step *k*, given an initial storage $x_k^b$ and time duration *T* is used to solve the following finite-horizon optimal control problem:

$$J(x_k^b) = \min_{\mathbf{u}_k^{T-1}} \sum_{j=0}^{T-1} \mathbf{c}_u'(k+j)\mathbf{u}(k+j) - OM^b\mathbf{F}'(k+j)\mathbf{u}(k+j) - OM^b\mathbf{f}'\mathbf{w}(k+j) + \mathbf{c}_z'\mathbf{z}(k+j)$$

subject to

storage model (9), variable $x^b(\cdot|k)$;

constraints (10), (11), (13);

constraints (16);

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$S_i.P_i(k+j) + s_i \leq \sigma_i(k+j); i = 1 \ldots N_g$

$$x^b(k|k) = x^b(k) \tag{17}$$

where $S_i$ and $s_i$ are already defined in (14). Here, we recall the disturbances profile's vector, $\mathbf{w}(k+j)$ represents the vector known over the prediction horizon, for $j = 0, \ldots, T-1$; thus the term $\mathrm{OM}^b\mathbf{f}'\mathbf{w}(k+j)$ does not affect the optimal solution of the objective function.

As per the receding horizon strategy, the optimal sequence $\mathbf{u}(k)$ is applied to the first element only. The new measured/estimated state $x^b_{k+1|k+1} = x^b_{k+1}$ is repeated at time $k+1$ of the optimization problem (17). The advantage of repeated online optimization is its feedback.

Note that the applied control scheme in this paper is assuming that the control decisions makes by controller are correct predictions.

### *F. Prodedure to solve Optimization Problem*

ON/OFF states and the power levels generated by the non-conventional generation units and the storage energy levels current state are initialized by the microgrid system model at each time . In this MPC problem is a MILP problem. Branch & Bound technique is applied to the MILP problem, because its solution is globally optimal [41], [42]. Optimization problem formulation was implemented using MATLAB. ILOG's CPLEX 12.0 was used to solve MILP optimizations since, it is an efficient solver based on branch & bound algorithm. All computations are done on an AMD E-350 processor, 1.60 GHz and 2.00 GB RAM.

## IV.SIMULATION STEP

Here, we consider a microgrid in grid-connected mode in the simulations which is shown in figure. 1; it comprises of PV plant with maximum power 16KW, four DG units, one energy storage, critical and controllable loads. Energy storage, bounded between 25 and 250 KWh is included with maximal charge and discharge rates 150 and -150KW; charge and discharge efficiencies are equal to 0.9, respectively. As the microgrid is in grid-connected mode power can be purchased or sold from/to the utility grid. As per European Energy Exchange (EEX on a certain day, the daily energy prices are shown in Figure. 3. with 1 hour sampling time and 24 hours planning horizon.

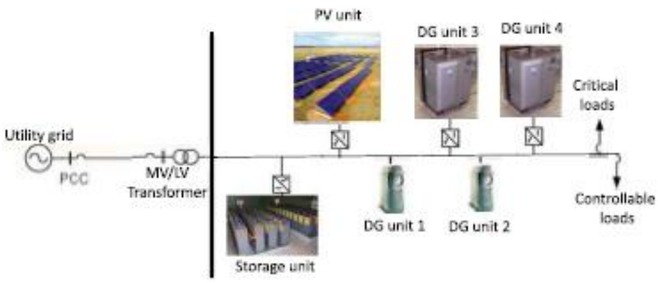


Figure.1. Scheme of microgrid considered in Case A and C simulations

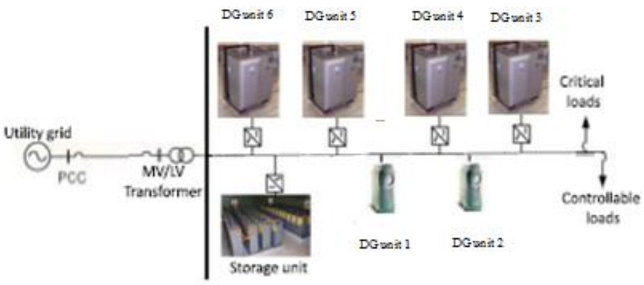


Figure.2. Scheme of microgrid considered in Case B simulations.

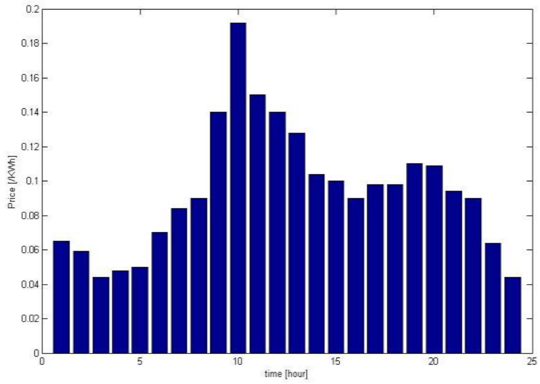


Figure.3. Spot energy prices

Here, we are considering three cases to compare the microgrid operation optimization based on different strategies.

*Case A:*

Based on the data provided in [38] and [44], the four DG unit parameters are described in Table IV. On considering above data we compare the following strategies for the microgrid optimization problem.

Table IV: Generator Parameters in Case A**.**

| DG Unit | $P_{min}$ | $P_{max}$ | $a_1$ | $a_2$ | $a_3$ |
|---|---|---|---|---|---|
| Unit 1 | 6 | 50 | 0.0013 | 0.062 | 1.34 |
| Unit 2 | 16.4 | 92 | 0.001 | 0.057 | 1.14 |
| Unit 3 | 16 | 90 | 0.0004 | 0.06 | 1.14 |
| Unit 4 | 12.3 | 72 | 0.0006 | 0.058 | 1.9 |

*1) MPC-MILP with storage and RES:*

MPC-MILP is a technique which also considers uncertainties through feedback loop. In this strategy we are considering all four DG units, storage and RES to meet the demand.

*2) MPC-MILP with storage and without RES:*

During Cloudy hours PV plant fails to generate energy. At this instant subsystem like microgrid will face power balance problems this leads to customer's discomfort. To study the behavior of the system at that moment, we temporarily detached the PV panel and observed optimization results.

*3) MPC-MILP without storage and with RES:*

In this section, we considered the without storage device and we observed microgrid optimization results.

*4) MPC-MILP without storage and RES:*

In this section, we detatched both non-coventional energy unit and storagedevice to observe the system behavior and optimization results.

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*CASE B:*

In this case we completely replaced PV unit with two DG units as shown in Figure. 2. On considering the additional DG units data and the above data as shown in Table V, we compared the microgrid optimization problem as follows:

Table V: Generator Parameters in Case B

| DG Unit | $P_{min}$ | $P_{max}$ | $a_1$ | $a_2$ | $a_3$ |
|---|---|---|---|---|---|
| Unit 1 | 6 | 50 | 0.0013 | 0.062 | 1.34 |
| Unit 2 | 16.4 | 92 | 0.001 | 0.057 | 1.14 |
| Unit 3 | 16 | 90 | 0.0004 | 0.06 | 1.14 |
| Unit 4 | 12.3 | 72 | 0.0006 | 0.058 | 1.9 |
| Unit 5 | 15 | 80 | 0.0002 | 0.023 | 1.5 |
| Unit 6 | 15 | 80 | 0.0002 | 0.023 | 1.5 |

*1) MPC-MILP Replacing RES with DGs (with storage):*

In this strategy only PV unit was replaced with DG units and observed the behavior of the microgrid system and optimization problem results.

*2) MPC-MILP Replacing RES with DGs (without storage):*

In this strategy along with PV unit storage device also dethatched to observe the system behavior and optimization results on considering DG units in the place of PV unit.

*CASE C:*

In this case we changed the four DG unit parameters as shown in Table VI, to study the behavior of the system and optimization problem. The strategies considered here same as Case A.

Table VI: Generator Parameters in Case C

| DG Unit | $P_{min}$ | $P_{max}$ | $a_1$ | $a_2$ | $a_3$ |
|---|---|---|---|---|---|
| Unit 1 | 150 | 600 | 0.001562 | 7.92 | 561 |
| Unit 2 | 100 | 400 | 0.00194 | 7.85 | 310 |
| Unit 3 | 50 | 200 | 0.00482 | 7.97 | 78 |
| Unit 4 | 20 | 100 | 0.024 | 8 | 80 |

*1) MPC-MILP with storage and RES:*

MPC-MILP is a technique which also considers uncertainties through feedback loop. In this strategy we considered all four DG units with new parameters, storage device and RES to meet the demand.

*2) MPC-MILP with storage and without RES:*

During Cloudy hours PV plant fails to generate energy. At this instant subsystem like microgrid will face power balance problems this leads to customer's discomfort. To study the behavior of the system at that moment, we temporarily detached the PV panel and observed optimization results.

*3) MPC-MILP without storage and with RES:*

In this section, we considered the without storage device and we observed microgrid optimization results.

*4) MPC-MILP without storage and RES:*

In this section, we detatched both non-coventional energy unit and storagedevice to observe the system behavior and optimization results.

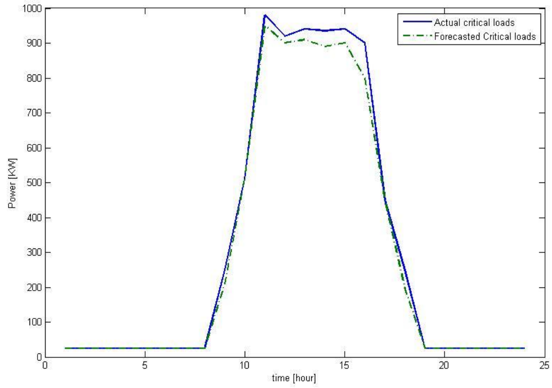


Figure.4. Forecasted and Actual demand over 24h.

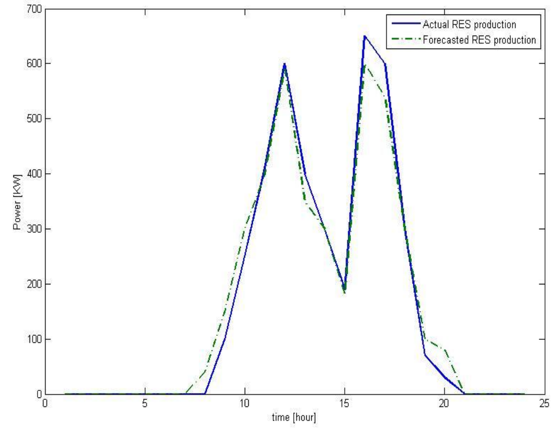


Figure.5. Forecasted and actual PV power generation over 24h.

To apply the Model predictive control strategy, computation of non-conventional power and demand forecasts have to be described. Support vector machines (SVMs) and neural networks (NNs) [45] are proposed methodologies for nonlinear forecasting. In [46],[47] SVMs is a powerful statistical method to capture the underlying structure in a data set on considering input training data. It is successfully applied for non-conventional energy prediction and demand forecast [48], [49].

In this paper, all the forecasts are obtained by MATLABs SVM toolbox, LS-SVM training and simulation environment written in C-code [51]. Examples of daily demand and non-conventional energy production profiles are employed in the optimization problem are shown in figures 4 and 5.

## V.SIMULATION RESULTS

Here, three cases experimental validation of MPC-MILP control algorithm are performed. We consider 1 h sampling period and the experiments are run over 24 h.

*Case A*

Figures 6, 7 and 8 show, respectively, the DG unit power generation, power exchanged with the utility grid and energy stored obtained by applying the different strategies.

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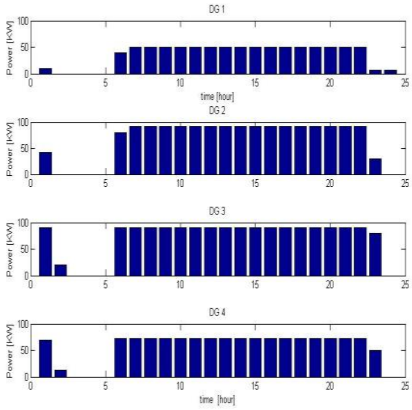


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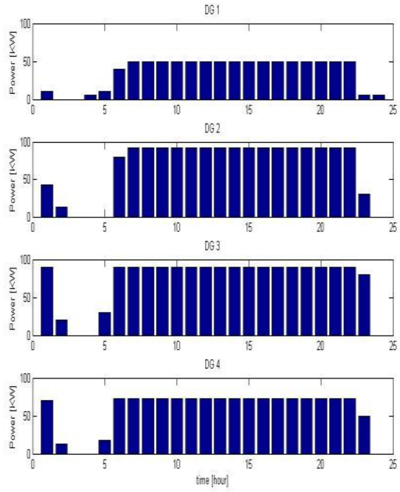
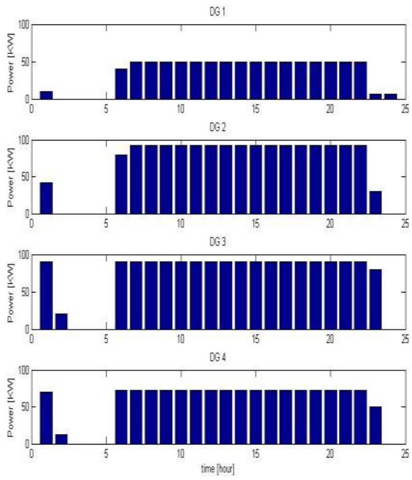
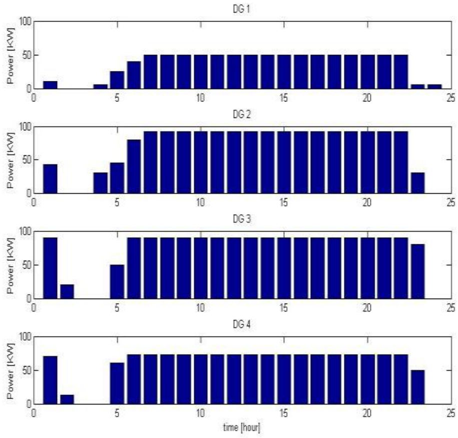



(b)

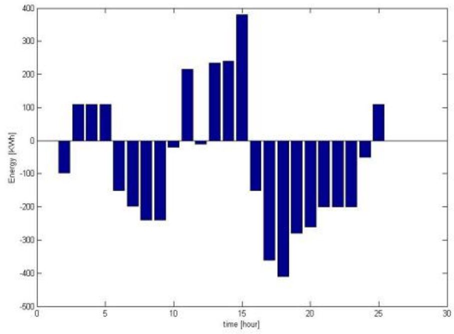



(c)

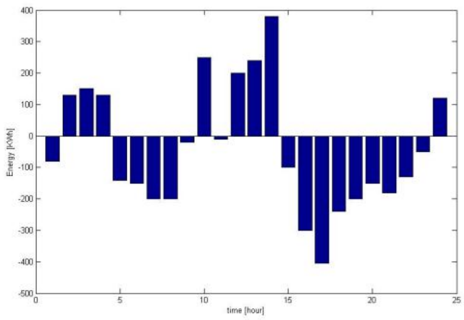



(d)

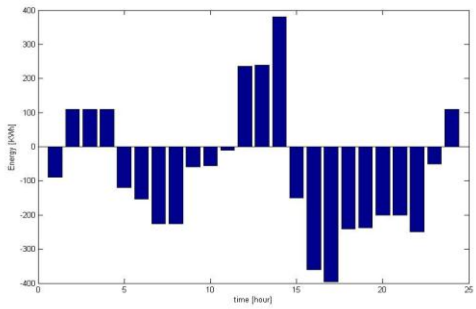
Figure.6. DG units power generation over 24h (MPC-MILP). (a) with storage with RES. (b) with storage without RES. (c) without storage with RES. (d) without storage without RES




(a)




(b)

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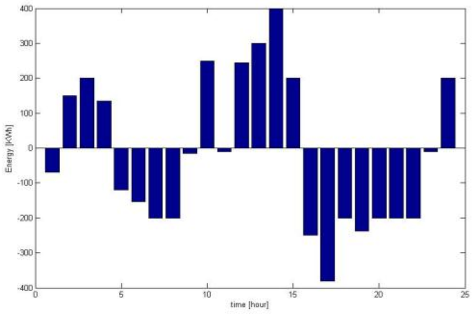
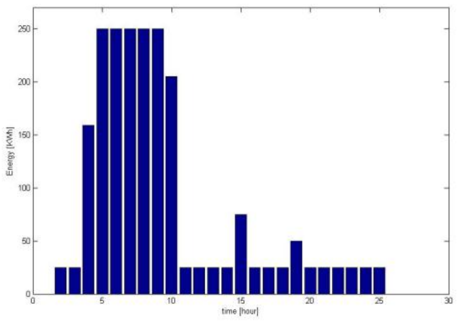
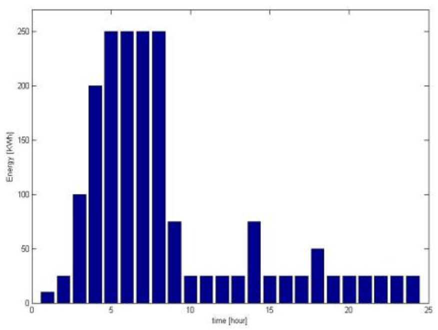



(d)

Figure.7. MPC-MILP based Purchased/sold energy over 24 hour. (a) with storage with RES. (b) with storage without RES. (c) without storage with RES. (d) without storage without RES




(a)

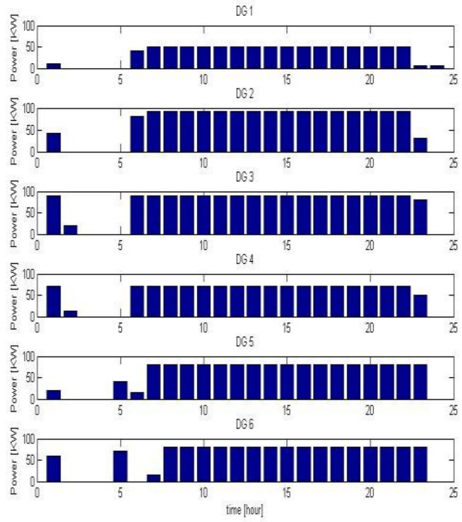



(b)

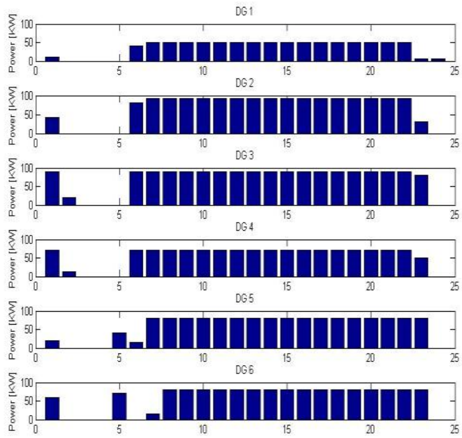
Figure.8. Energy stored over 24h (MPC-MILP). (a) with storage with RES. (b) with storage without RES.

*Case B*

As per this case, by replacing PV plant with two DG units coding was simulated. Figures 9, 10 and 11 show, respectively, the DG unit power generation, power exchanged with the utility grid and energy stored obtained by applying the different strategies.

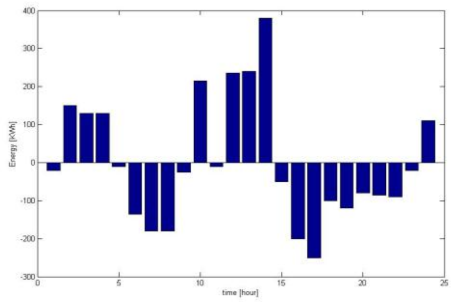



(a)




(b)

Figure.9. DG units power generation over 24h (MPC-MILP). (a) Replacing RES with DGS with storage units. (b) Replacing RES with DGS without storage units.




(a)

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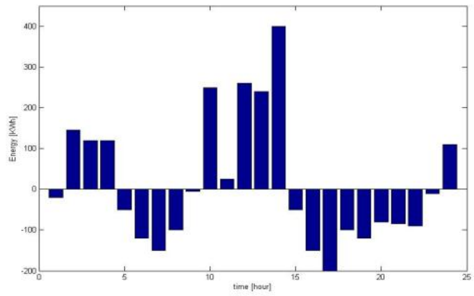



(b)

Figure.10. MPC-MILP based Purchased/sold energy over 24hour. (a) Replacing RES with DGs with storage units. (b) Replacing RES with DGs without storage units.

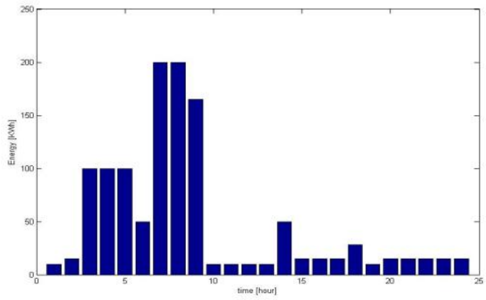
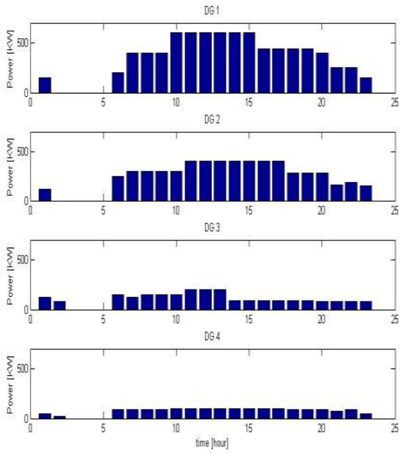



Figure.11. Energy stored over 24h (MPC-MILP) replacing RES with DGS with storage units.

*Case C*

By changing generator parameters of case A with standard data, program was simulated. Figures 12, 13 and 14 show, respectively, the DG unit power generation, power exchanged with the utility grid and energy stored obtained by applying the different strategies.

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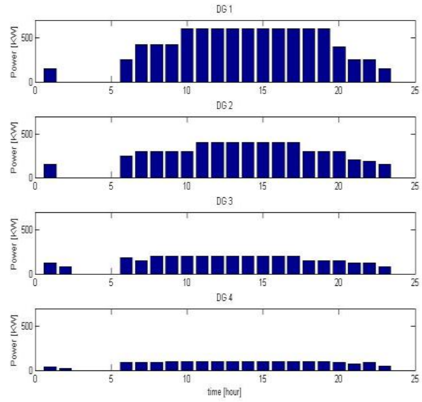


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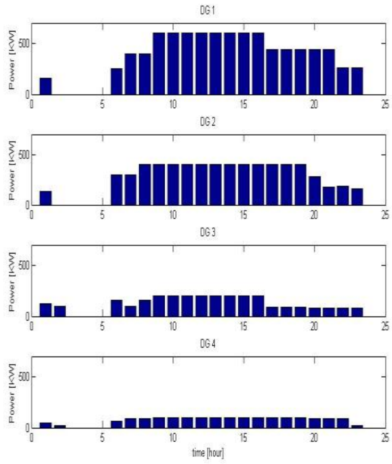
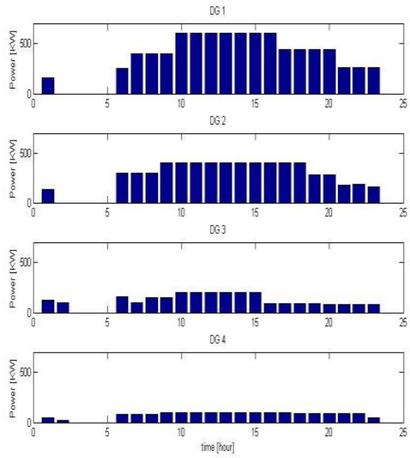



(c)




(d)

Figure.12. DG units power generation over 24h (MPC-MILP). (a) New DGs with storage with RES. (b) New DGs with storage without RES. (c) New DGs without storage with RES. (d) New DGs without storage without RES

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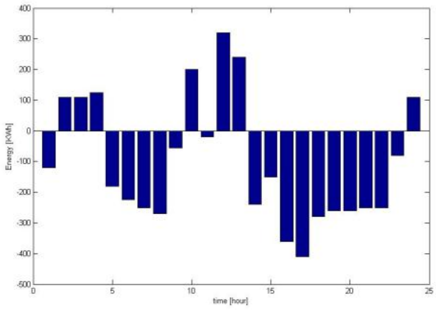
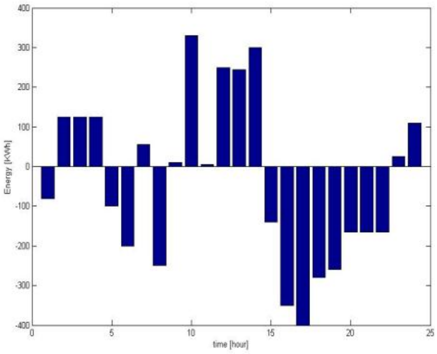


(a)



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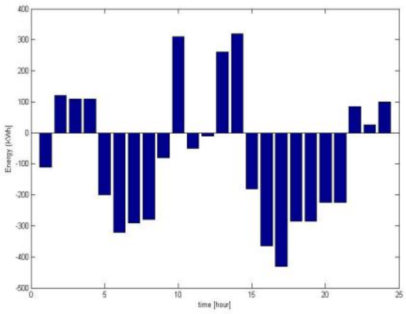

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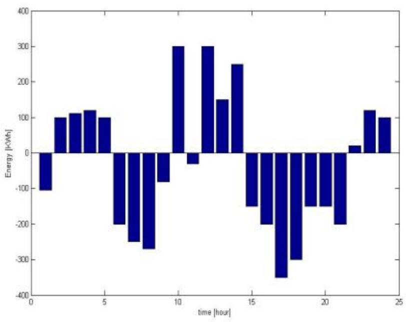
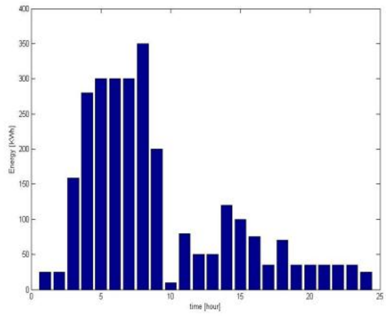
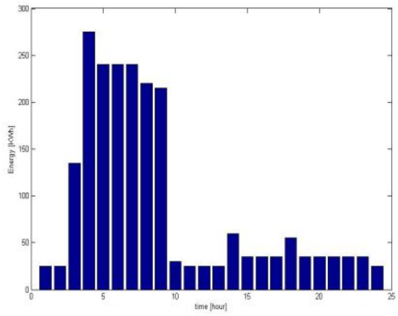


(d)

Figure.13. MPC-MILP based Purchased/sold energy over 24 hour. (a) New DGs with storage with RES. (b) New DGs with storage without RES. (c) New DGs without storage with RES. (d) New DGs without storage without RES



(a)



(b)

Figure.14. Energy stored over 24h (MPC-MILP) (a) New DGs with storage with RES. (b) New DGs with storage without RES.

Table VII: Comparison of Microgrid Operation with different strategies considered in Case A

| S.No | Strategy | Total Costs (€) |
|---|---|---|
| 1 | MPC-MILP with storage with RES | 403.3 |
| 2 | MPC-MILP with storage without RES | 439.7 |
| 3 | MPC-MILP without storage with RES | 418.9 |
| 4 | MPC-MILP without storage without RES | 452.1 |

Table VIII: Comparison of Microgrid Operation with different strategies considered in Case B

| S.No | Strategy | Total Costs (€) |
|---|---|---|
| 1 | MPC-MILP replacing RES with DGS with storage units | 496.3 |
| 2 | MPC-MILP replacing RES with DGS without storage units | 515.4 |

Table IX: Comparison of Microgrid Operation with different strategies considered in Case B

| S.No | Strategy | Total Costs (€) |
|---|---|---|
| 1 | MPC-MILP New DGs with storage with RES | 628.2 |
| 2 | MPC-MILP New DGs with storage without RES | 665.9 |
| 3 | MPC-MILP New DGs without storage with RES | 643.5 |
| 4 | MPC-MILP New DGs without storage without RES | 679.9 |

From the simulation results, Table VII, VIII & IX reports the performance of the described cases for microgrid operation optimization. It shows that the cost increment with respect to the cases considered in this paper. Moreover, it also reports that a storage and PV plant unit makes the microgrid more economically more efficient.

## CONCLUSION

In this paper, a Model Predictive control is considered for MILP optimization problem to the study behaviour of the microgrid system during uncertainties while satisfying operational constraints and a time varying requests The overall problem includes modelling of storage devices, demand side policies and so on. It also accounts the unit commitment, economic load dispatch, selling and purchasing of energy to/from the utility grid. The optimization problem further copes with uncertainties of non-conventional energy sources, energy prices and demand. The MPC approach is proposed to cope with the above uncertainties. MPC-MILP framework is used to formulate the Overall optimization problem and commercial solvers are used for substantial improvements in solution quality and computational burden. A microgrid case study is employed to know its working strategy during online optimization and the simulation results are discussed. A modification for above case study was done by considering three cases by assigning uncertainties of non-conventional energy resources and storage device. The results show that a storage and PV plant unit makes the microgrid more economically more efficient.

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