***Long Term Pump Storage Capacity Planning for Microgrid in Model Predictive Control Platform***

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*Abstract*— This work considers the optimal long term pumped storage capacity problem for a microgrid equipped with a Wind Farm (WF), Interruptible Loads (IL), transmission line to a main grid and Pump Storage (PS). Typically, the WF is operated according to wind speed to charge PS and supply electrical power to satisfy the load demands. A linear model is established to describe the system dynamics of the central plant. A model predictive control (MPC) problem is formulated to obtain optimal set points to satisfy the consumer demands and minimize daily operation cost. At each 24 hour time scale, the MPC problem is represented as a large-scale mixed-integer linear programming (MILP) problem. After solving the MILP for 26 years, we propose a financial algorithm to obtain best capacity for the PS in longevity. Simulation results clearly show how much IL cost should be expected for different amounts of pumped storage capacity. A comparison between the operating and investment costs is then used to determine the optimal pumped storage capacity. Finally, various sensitivity analyses are performed to assess the effect of key parameters on this optimal capacity.

Keywords—capacity planning; pump storage; MPC; windfarm; longterm.

#  Introduction

According to the Renewable Energy Organization of Iran [1], around 29.3PWh of energy was consumed in 2008. 87% of the energy was from petroleum while 50% of the petroleum was imported around 1.32 million tons/day. From 2006 to the present, the price of gasoline has fluctuated due to the instability in the Middle East, manipulation of energy supplies, competition over energy sources, attacks on supply infrastructure, and natural disasters. To improve the nation’s energy independence and security, the best solution is to efficiently utilize renewable energy resources including solar, wind, hydro, geothermal, and tidal energy. Installed wind power capacity has increased substantially over the last decade over the world. In Iran for example, the installed wind power generation capacity reached 91 MW by the end of 2011 and is planned to reach 4.5 GW by the end of 2025.

The stochastic nature of wind generation increases the fluctuation and the uncertainty on the net load. When wind generation makes up a large proportion of the committed generation capacity, minimum load problems can arise when thermal generating units cannot operate at a much reduced output or cannot be stopped. Thereupon, we need fast and low speed storages to be coordinated with our microgrid to intelligently control the fluctuation of Wind Generation (WG).

A perfect review on the operating system of four types of energy storage system and their capability to stabilize grid system in different ways based on their storage characteristic did in [2]. During this review, this fact reveals that for smoothing power fluctuation of WG and for save abundant amount of energy we need for instance flywheel or super capacitor for their high speed reaction and battery respectively. Nevertheless PS can influence on the microgrid as both parts that discussed. Pumped storage facilitates the operation of a power system in several ways:

1) By storing energy during periods of low load and generating during periods of high load, it reduces the overall system cost by increasing the base load and shaving the peak load.

2) It provides operating reserve more economically than thermal generation operating at a low utilization factor.

3) It provides some of the flexibility needed to compensate for the fluctuations in the wind power, thus avoiding extra ramping costs for conventional units and spilled wind energy.

4) It contributes to frequency and voltage control.

Recently, MPC has drawn the attention of the power system community due to several factors: 1) it is based on future behavior of the system and predictions, which is attractive for systems greatly dependent on demand and renewable energy generation forecasts; 2) it provides a feedback mechanism, which makes the system more robust against uncertainty; and 3) it can handle power system constraints, such as generator capacity and ramp rate constraints. As we consider our optimization base on MPC-MILP framework.

According to properties of motor and generator in the structure of PS we can plan the operation of microgrid.

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| **CONTROLLER (MPC)**$$P\_{IL}^{best}$$$$P\_{WC}^{best}$$$$P\_{grid}^{best}$$$$P\_{charge}^{best}$$*Load Forecasting*$$P\_{Load}$$$$P\_{WG}$$*Wind speed Modeling***Microgrid**Wind FarmPump-StorageLoadConnection With Grid |
| Fig. 1. Model of system |

## Literature Review

Our research compose of two main parts: 1. Microgrid operation optimization base on MPC framework, and 2. Financial decision for PS capacity. Thereupon our early research was based on aforementioned part.

Due to the microgrid optimization problem complexity and because of the large economic benefits that could result from its improved solution, considerable attention is being devoted to the development of better optimization algorithms and suitable modeling frameworks. Metaheuristics and heuristics have been proposed to solve the power dispatch problem for microgrids, such as genetic algorithms [3], evolutionary strategies, and tabu search algorithms [4]. Studies have suggested that microgrids can achieve high performance through: 1) advanced control algorithms accounting for system uncertainty and based on predicted future conditions; 2) deployment of demand response; 3) optimal use of storage devices in order to compensate the physical imbalances; and 4) applying optimal instead of heuristic based approaches [5]-[7]. Further, in the aforementioned works, either the optimization problem stays nonlinear or other important features, such as demand side programs or IL, are neglected. In some research a long term planning for PS capacity analyze in one year and did not consider a life of PS in next year [8].

Some works can be found in the literature that address MPC for optimal dispatch in power systems. The authors in [9] model a combined cycle power plant by utilizing hybrid systems in order to describe both the continuous/ discrete dynamics and the switching between different operating conditions. Then the plant operations are economically optimized through MPC by taking into account the time variability of both prices and electricity/steam demands.

 Ferrari–Trecate et al. [9] propose an MPC algorithm to solve the economic dispatch problem with large presence of intermittent resources. However, many microgrid key features, such as demand side programs, storages and ON/OFF generators status are not considered. In [10] and [11], an MPC is applied to managing the energy flows inside a household system equipped with a micro combined heat and power unit. In addition, the household can buy and sell electricity from/to the energy supplier and heat and electricity can be stored in specific storage devices. Hooshmand et al. [12] and Xia et al. [13] apply an MPC framework to solve the dynamic economic dispatch, which aims at minimizing the generation cost over a particular time interval (the dispatch interval). Then, the goal is to decide the power dispatch in order to meet the demand at minimum cost subject to limits on power generation and

ramp rates.

Eventually, we would like to remark that when storage elements are considered, generally the storage is modeled as a discrete-time first-order system with two continuous variables representing charging and discharging power multiplied by suitable, and different, charging and discharging efficiencies. That approach does not rule out the possibility that the optimal solution contemplates simultaneous charging and discharging of the storage, a physically unrealizable policy. Such outcome may occur as the mathematical consequence of unpredicted Renewable Energy Source (RES) generated power surplus, bounds on the exchanged power with the utility grid, and costs of the storage level. This issue has been never discussed in the corresponding studies. Because of the different multiplicative factor in charging and discharging, one continuous variable, which can take both positive and negative values, cannot represent correctly the storage behavior. Similarly the interaction with the utility grid should be modeled so as to prevent simultaneous selling and purchasing under certain market circumstances.

## Main Assumptions

In a supposed microgrid control structure, several assumptions should be addressed:

1) The optimization has the option to consider load shedding but this incurs a penalty set at CIL RMB to make load shedding a last resort for the optimization. This penalty is included in the operating cost. Furthermore, none of the last case studies performed required load shedding.

2) The high level controller deals with the long-term (1hour) behavior of the system and is very weakly dependent on the transient behavior of the fast dynamics. Then, a steady state assumption for microgrid components can be safely made without much loss of accuracy.

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| Fig. 2. Load variation for 2020-2045 |

4) Since the proposed methodology is designed to simulate dispatching under normal conditions, forced outages of conventional generation are not considered.

5) The microgrid high level controller has knowledge of the managed network; it knows the existing generation capacity, storage capacity, network constraints, market energy prices, and bilateral contracts.

6) The microgrid operator is the unique entity in charge of management, aimed at optimizing cost. It can take economic decisions, such as to sell or buy energy depending on local generation capabilities and costs and the energy prices.

7) Due to constant sampling time t, there exists a constant ratio between energy and power at each interval.

8) Our load and energy forecasting approach is capable of making long-term forecasts. However, unlike other long term forecasting models, the proposed method produces hourly results with improved accuracy.

9) We suppose wind speed behavior repeat every year and we can use one pattern for our planning.

10) Price of power during planning horizon is a constant three level value for a day, it means three different prices depend on hour of day exist here for optimization.

11) Microgrid’s PS has set of motors and generators with equal rated power.

## Main Contributions

We focus on a MPC base on MILP framework for optimize the operation cost to form a long term capacity planning problem of a microgrids’ PS. In this project a operative long term load forecasting that use for one hour demand was employed. Moreover the development of a novel model of the overall microgrid system adopting a formalized modeling approach, which is suitable to be used in online optimization schemes for minimizing the microgrid running costs as the presentation of simulation results showing the effectiveness of the proposed optimization routine. The other main contribution of our work is employing effective financial method. Net Present Value (NPV) is a finance method that can change every year cost or profit to reference time.

## Outline

This paper is further organized as follows: 1) the microgrid system is described and the its’ modeling approach is outlined in Section II; 2) the operations optimization, PS planning scenario and financial computation are debated in Section III; 3) some simulation results are discussed in Section IV; and 4) finally, conclusions are drawn in Section V.

## Numenclature

The forecasts, the parameters and the decision variables used in the proposed formulation are described, respectively, in Tables I–III, where, for simplicity, we omit the subscript *i* when referring to the *i*th unit. In the following sections, vectors and matrices are denoted in bold.

# SYSTEM MODEL

## Loads

A chronological load curve for 26 years (2020-2045) is required for the simulation. The load curve in 2020 was generated based on the long-term load forecast [14] by the actual load profile is for 2003-2014. Fig. 2 shows typical hourly load curves for 26 years. The maximum load happens in summer and the minimum load during the spring holiday. This minimum load is then only about one third of the summer peak loads because most industrial loads are turned off.

In general, we consider two types of loads:

1) Critical loads, i.e., demand levels related to essential processes that must be always met;

2) Interruptible loads, i.e., loads that can be reduced or shed during supply constraints or emergency situations (e.g., low wind speed, day-time lighting). In demand response programs, the customers specify level of curtailment of the controllable loads. The IL have a preferred level, but their magnitude is flexible so that the demand level can be lowered when it is convenient or necessary (e.g., in islanded mode). This leads to users’ discomfort, hence a certain cost is associated with the load curtailment/shedding (a penalty for the microgrid). We define quadratic function for penalty of load curtailment. Since experience has shown that mixed integer linear programs are computationally more efficient than quadratic programs, the penalty cost function of an IL defined as:

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| $$C\_{IL}=aP\_{IL}^{2}+bP\_{IL}+c$$ |  |

And is approximated by the max of affine functions without introducing binary variable [15]

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| $$C\_{IL}\left(P\_{IL}\right)=max\left\{S.P\_{IL}+s\right\}=\left‖S.P\_{IL}+s\right‖\_{\infty }$$ |  |

Where *P* is the generated power, and *S* and *s* are obtained by linearizing the function at *n* points. Load curtailment penalty per kilowatt is considered for each season in year. Fig. 3 shows these penalty periods relevant to consumers demand.

## Pump Storage Dynamic

We employ two-reservoir PS model developed in [8], where the state of PS is captured by the top-tank water height. The model is further simplified by ignoring the time delays of the PS tank output. We also assume that the PS motor and generator is always reliable. The PS cistern operates in two modes. In the charging mode, water from the underneath bank is supplied to the upside bank, while in the discharging mode water from the upside go to the bottom. The mode is denoted by $P\_{PS}$.

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| $$P\_{PS}\left(t\right)=\left\{\begin{array}{c}negative, \&Generating\\positive, \&Pumping\end{array}\right.$$ | (3) |

For storage unit, denoting by $x\_{PS}(t)$ the level of the energy stored at time t and by $P\_{PS}(t)$ the power exchanged with the storing device at time t, we consider the following discrete time model of a storage unit:

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| $$V\_{PS}\left(t+1\right)=V\_{PS}\left(t\right)+ηP\_{PS}\left(t\right)-V\_{PS}^{d}$$ | (4a) |

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| $$η=\left\{\begin{array}{c}η^{c}, \&Generating\\\frac{1}{η^{d}}, \&Pumping\end{array}\right.$$ | (4b) |

$0<η^{c},η^{d}<1$The charging and discharging efficiencies account for the losses and $V\_{PS}^{d}$ denotes a constant stored water degradations, for instance evaporation, in the sampling interval.

## Interaction With the Utility Grid

The microgrid is tied to the grid at the point of common coupling (PCC) where power goes through a step up transformer before moving upstream to be converted from AC to AC. At this point, the power flow balance is considered.

In the objective function discussed in section III, $P\_{grid}(t)$ is the power schedule at the PCC at time t and can take on both positive and negative values. A simple power limiter also caps the amount of power that can be transmitted over the line and we model this as $\left|P\_{grid}(t)\right|\leq P\_{PCC}$ where $P\_{PCC}$ is the power limit at the PCC.

## WF Operating Condition

As we expressed our planning base on this assumption the unique wind speed pattern recur every year and we have one WG in 19th hour of 17 Jun 2029 and 2039. Examples of one year wind speed profiles routine are shown, in Fig. 4. As the figure depicted average of wind speed in spring and summer is more than in autumn and winter and then can be generated more power in these seasons. Total average of wind speed during a year is 10 m/s.

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| MidnightNoon10PM7AM**Weekends/Holiday**Midnight10PM**Weekdays**Noon8PM2PM7AM**SHOULDER****OFF-PEAK****PEAK****OFF-PEAK****SHOULDER** |
| Fig. 3. Three energy cost periods for weekdays and weekends/holidays inNSW region |

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| Fig. 4. Wind speed variation of year 2021 |

# OPTIMIZATION PROBLEM

## Cost Function

The system has two primary objectives, namely to provide energy arbitrage from intermittent wind farm output and secondary objective is also included to minimize cost function.

The total cost incurred at each time step is denoted as $COST(P\_{WG}(t),P\_{Load}(t))$ where $R^{2n+1}→R∪\left\{\infty \right\}$ is a convex stage function. Because our objective is distinct, we can consider a cost function that is equal to the sum of the system

individual costs and profits with positive or negative signs.

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| $$J=\sum\_{t=0}^{T-1}cost\left(P\_{WG}(t),P\_{Load}(t)\right)=cost\left(P\_{grid}\left(t\right)\right)+cost\left(P\_{IL}\left(t\right)\right)+cost\left(P\_{WC}\left(t\right)\right)$$ | (5) |

## Capacity and Terminal Constrains

To pose the final MILP optimization problem, additional operational constraints must be met

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| $$V\_{PS}^{min}\leq V\_{PS}(t)\leq V\_{PS}^{max}$$$$P\_{PS}^{min}\leq P\_{PS}(t)\leq P\_{PS}^{max}$$$$\left|P\_{IL}\left(t+1\right)-P\_{IL}\left(t\right)\right|\leq ∆P\_{IL}^{max}$$ | (6a)(6b)(6c) |

The constraints above model the physical bounds on the storage device (6a), the power flow limits of the PS motor and generator (6b), and the bounds on controllable loads curtailments (6c).

## MPC problem

Model predictive control (MPC) is a control policy that allows us to set up a framework that we use to dynamically and robustly control and schedule the microgrid. Within the MPC framework, the model of our system from Section II is solved as an optimization problem in real time at each time step to determine an action policy and enable scheduling of PS, ILs and WC over the finite MPC time horizon. The controller uses predictions (for consumer demand) and actual (for WG) data to help determine the local control actions of each device.

Although a formal statistical or stochastic model can be used to represent uncertainty when making predictions, it is not needed for the policy to work and the controller can often perform very robustly even when predictions are poor. The first step in MPC is to solve the optimization problem at the current time step and determine conditional power schedules over a fixed time horizon extending T steps into the future. The solver uses the information available to it locally along with predictions of unknown quantities to minimize the MPC objective function subject to the constraints of the microgrid structure elements and power converters as well as the constraints at the PCC.

The optimization problem we solve, is similar to the one specified in Section II but over a finite time horizon. Using the modeling approach of Section II, the problem can be formulated as a MILP optimization problem, which generates an optimal plan. The single MILP is an open loop solution, which does not account for these uncertainties. A possible remedy is to embed MILP optimizations within an MPC framework, so that a feedback control law can be implemented and the uncertainty can be potentially compensated. In absence of uncertainty, these two solutions coincide [15].

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| $$\frac{1}{T}\left[\sum\_{t=T}^{T+24}α\_{ex}\left(t\right).P\_{grid}\left(t\right)+S\left(t\right).P\_{IL}\left(t\right)+ω\_{WC}P\_{WC}(t)\right]+s$$ | (7) |

The MPC optimization problem is a MILP problem. The branch-and-bound techniques are mostly applied to MILP problems [16]. The main advantage of the branch and bound method is that if a solution is reached, the solution is known to be globally optimal.

At every time step T, with solving this equation, the microgrid controller must take high level decisions about:

* How much curtailment should wind farm to meet this load at minimum demand (unit commitment);
* When should the PS been charged or discharged;
* When and how much energy should be purchased from or sold to the utility grid (when the microgrid is in the grid-connected mode);
* Curtailment schedule (which controllable loads must be shed/curtailed and when);
* How much energy has to be stored.
* Indeed our controller action consists of three elements vector in every hours $u=\left[P\_{grid},P\_{IL},P\_{WC}\right]$.

## Financial Formulation

For an isolated system, the capacity of WG should be able to meet the maximum assigned power. Usually, there must be some reserve capacity for the PS to deal with the uncertainties or prediction errors of renewable energy. The determination of reserve capacity is not the focus of this work, but we want conclude an effective PS capacity for planning horizon by financial computations. Indeed we use NPV method to change operation cost of microgrid value and compose it with capital cost as follows:

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| $$COST\_{microgrid}=CAPITAL COST\_{PS}+\sum\_{Y=2020}^{2045}NPV(operation cost(Y))$$ | (8) |

As:

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| $$NPV\left(operation cost\left(Y\right)\right)=operation cost(Y)\frac{\left(1+i\right)^{Y}-1}{i\left(1+i\right)^{Y}}$$ | (9) |

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| Fig. 5. Microgrid operation cost of 2021 |

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| Fig. 6. NPV of year operation cost |

# Simulation results

## Case Study

We demonstrate the hourly cost minimization capabilities of the MPC algorithm on a grid tied wind farm-storage system using data and specifications taken from the[12].

The supposed system is connected to the grid at the PCC through a power converter with a bidirectional meter and control system which has access to real-time prices. The connection also has a physical power transfer limit$P\_{grid}^{max}=1000kW$. The system takes measurements and data at 1 hour intervals at all points of the system, including the power output of the WF turbine and the output at the PCC. We incorporate this into the model described in Section II as historical data and use MPC to enable optimization and scheduling of the PS unit. Since the maximum output of the WF turbine is 50 kW, any excess wind speed blowing on the turbine must be dumped.

Due to the equivalent technical characteristics of PSs’ motor and generator, the pumping rate and generating rate are assumed to be equivalent. Since the degradations efficiencies are near unity, we use 4m3 for $V\_{PS}^{d}$. We choose the initial state of PS unit to be 50% of the nominal capacity. The parameters of each other element along with the system specifications and parameters are summarized in Table II below.

## Simulation Details

The formulation presented in Section III-F was implemented using MATLAB. We used ILOG’s CPLEX 12*.*0 (an efficient solver based on the branch-and-bound algorithm) to solve the MILP optimizations. All computations are done on an Intel Core 2 Duo CPU, 2 GHz.

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| ***Parameter*** | ***Description*** | ***Value*** |
| $$P\_{PCC}^{max}$$ | Maximum power output of microgrid | 2000kW |
| $$P\_{WG}^{max}$$ | Maximum power output of WF turbine | 50kW |
| $$C\_{PS}=D\_{PS}$$ | Maximum pumping and generating rate of motor and generator | 250kW |
| $$η^{c}$$ | Pump efficiency of motor | 0.70m3/kW |
| $$η^{d}$$ | Generate efficiency of generator | 0.95kW/m3 |
| $$V\_{PS}^{d}$$ | Constant efficiency of degradation | 4m3 |
| $$P\_{IL}^{max}$$ | Maximum load curtailment | 100MW |
| $$S\_{peak}$$ | Curtailment penalty of peak hours | 0.43$/hour |
| $$S\_{off\\_peak}$$ | Curtailment penalty of off-peak hours | 0.37$/hour |
| $$S\_{shoulder}$$ | Curtailment penalty of shoulder hours | 0.24$/hour |
| s | Cost of contract to consumer for load curtailment | 250$/kWhour |

## Results and Discussion

The proposed objective optimization has been solved using the MILP algorithm in Matlab to obtain the optimum solution that minimizes the microgrid owner’s cost.

The daily spot prices (from the sum of hourly price, on a certain day in year 2021) are shown in Fig. 5. For simulation study, choose a sampling time of 1 h and a prediction horizon of 24 h. Simulations are performed over one day. In summer and winter the costs of microgrid operation are more than days in spring and autumn. This fact is due to the summer and winter peak and proper wind speed in spring that generates more wind power.

Table II. MICROGRID PARAMETERS

As depicted in fig. 6 since the interest rate is supposed to be 12.5%, clearly the present value of operation cost should be lower than this value to be rational.

As mentioned before, this objective function is dependent on each element seriously in a way that the reduction of one of them results in decreasing the other ones. In order to find the optimum solution, different values of the PS capacity are considered and the optimum solution for each respective capacity is calculated according to the formulation described in Section III. The data associated with each solution are showed in Figs. 7, 8. In these figures, for each capacity, the value of operational indices, capital cost indices, and their sums are given. In other words, the investment rate that would make the present value of future cash flows plus the final capital cost value of an investment is equal to the present total cost. In order to judge whether an investment is worthwhile, this term is calculated. In fig. 8 the value of present total cost decreases up to 35MW and then increases. Thus the optimal capacity for 26 years planning is 35 MW.

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| Fig. 7. Operation and investment costs for different amounts of installedpump storage capacity. |

## Sensitivity Analyzes

In this section, the model can analyze the effects of parameter variations. Our optimization finds out the optimal values for the different IR and IL penalty of the equipment that is considered in the microgrid and the associated constraints. The sensitivity variables are those variables which have been entered by the planner and have different values.

The main objective of using the sensitivity analysis in this work is that if the user isn’t sure which is the best value of a particular variable, then the user will enter different values and the sensitivity analysis will show how the results behave dependent on these values.

* Effect of IR

Fig. 9 shows that increase in IR has a significant effect on the total cost. From a base IR of 12.5% when the total cost is $7.375×10^{4} RMB$, the total cost decreases almost linearly as a function of the IR. At a IR of 20%, the cost decreases to $7.212×10^{4}RMB$, which is a 2.3% decrease in cost for a 7.5% increase in IR. However, it may be noted that increase in IR cannot significantly reduce the optimal value of PS capacity by altering the operation cost and its value fix at 35 MW during variation of IR.

* Effect of IL penalty cost

As we said in the assumptions the IL penalty costs are a fix range during the operation years and don’t vary during the time. But if we supposse we putin high or low price to consumer in the beginning of the contract the optimal PS capacity varies for the result of change in operation cost of our planning. Fig. 10 shows the variations of total cost function of PS capacity with different values of IL penalty cost. As we see the optimal capacity not a fix point and, indeed the planner decide best value for it. For example if IL penalty costs decrease 3% best capacity for PS is 40 MW.

# Conclusion

This paper presents the optimal planning for pump storage capacity and comparative studies for a microgrid compose of

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| Fig. 8. Sum of the operating and investment costs as a function of the pumped storage capacity. |

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| Fig. 9. Effect of the IR on the sum of the operating and investment costs for different amounts of installed pumped storage capacity. |

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| Fig. 9. Effect of the IL penalty cost on the sum of the operating and investment costs for different amounts of installed pumped storage capacity. |

complex structure such as wind farm, interruptible load and connection with main grid.

In firs part of our planning, we propose a novel mixed integer linear approach on modeling and optimization of microgrids. We bring into account unit commitment, economic dispatch, energy storage, sale and purchase of energy to/from the main grid, and curtailment schedule. First, we assume perfect knowledge of the microgrid state, renewable resources production, future loads, and so on, which is useful to solve the optimization problem. Further, to cope with inevitable disturbances and forecast errors, we embed this into an MPC framework. The proposed approach was investigated on a case study microgrid. Simulation results show that our MPC MILP control scheme is able to economically optimize the microgrid operations and save money. Second part consists of financial computation of operation cost and capital cost for PS. We find an optimal capacity that minimizes the total cost of microgrid

for upcoming 26 years. Our sensitivity analyzes depicted that optimal capacity of PS don’t fluctuate during the variation of IR or IL penalty.

##### References

1. www.suna.org.ir
2. Nor Shahida Hasan, Mohammad Yusri Hassan, Md Shah Majid, Hasimah Abdul Rahman. Review of storages schemes for wind energy systems. Renewable and Sustainable Energy Reviews 21(2013) 237-247.
3. G.-C. Liao, “Solve environmental economic dispatch of smart microgrid containing distributed generation system—Using chaotic quantum genetic algorithm,” Electr. Power Energy Syst., vol. 43, no. 1, pp. 779–787, 2012.
4. A. Takeuchi, T. Hayashi, Y. Nozaki, and T. Shimakage, “Optimal scheduling using metaheuristics for energy networks,” IEEE Trans. Smart Grid, vol. 3, no. 2, pp. 968–974, Jun. 2012.
5. R. Firestone and C. Marnay, “Energy manager design for microgrids,” Lawrence Berkeley Nat. Lab., Berkeley, CA, USA, LBNL Rep. LBNL- 54447, 2005.
6. A. Siddiqui, C. Marnay, O. Bailey, and K. LaCommare, “Optimal selection of on-site power generation with combined heat and power applications,” Int. J. Distrib. Energy Resour., vol. 1, no. 1, pp. 33–62, 2005.
7. G. Pepermans, J. Driesen, D. Haeseldonckx, R. Belmans, and W. D’haeseleer, “Distributed generation: Definition, benefits and issues,” Energy Policy, vol. 33, no. 6, pp. 787–798, 2005.
8. Ning Zhang, Chongqing Kang, Daniel S. Kirschen, Qing Xia, Weimin Xi, Junhui Huang, and Qian Zhang, “Planning Pumped Storage Capacity for Wind Power Integration,” IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, VOL. 4, NO. 2, 2013
9. G. Ferrari-Trecate, E. Gallestey, P. Letizia, M. Spedicato, M. Morari, and M. Antoine, “Modeling and control of co-generation power plants: A hybrid system approach,” IEEE Trans. Control Syst. Technol., vol. 12, no. 5, pp. 694–705, Sep. 2004.
10. R. Negenborn, M. Houwing, J. D. Schutter, and J. Hellendoorn, “Model predictive control for residential energy resources using a mixed-logical dynamic model,” in Proc. IEEE ICNSC, Okayama, Japan, Mar. 2009, pp. 702–707.
11. P. Kriett and M. Salani, “Optimal control of a residential microgrid,” Energy, vol. 42, no. 1, pp. 321–330, 2012.
12. A. Hooshmand, H. Malki, and J. Mohammadpour, “Power flow management of microgrid networks using model predictive control,” Comput. Math. Appl., vol. 64, no. 5, pp. 869–876, 2012.
13. X. Xia, J. Zhang, and A. Elaiw, “A model predictive control approach to dynamic economic dispatch problem,” in Proc. IEEE Bucharest Power Tech Conf., Bucharest, Romania, Jun./Jul. 2009, pp. 1–7.
14. Ümmühan Bas\_aran Filik, Ömer Nezih Gerek, Mehmet Kurban, “A novel modeling approach for hourly forecasting of long-term electric energy demand,” Energy Conversion and Management 52 (2011) 199–211.
15. [15] Alessandra Parisio, Evangelos Rikos, and Luigi Glielmo, “A Model Predictive Control Approach to Microgrid Operation Optimization,” IEEE TRANSACTIONS ON CONTROL SYSTEMS TECHNOLOGY, In press.
16. . Bertsimas and J. Tsitsiklis, Introduction to Linear Optimization. Belmont MA, USA: Athena Scientific, 1997.