APPLICATION OF EXTENDED LINEAR MODEL PREDICTIVE CONTROLLER FOR VOLTAGE AND FREQUENCY CONTROL IN MICROGRID

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Abstract: *Extended linear model predictive controller (ELMPC) is used in an isolated microgrid for voltage and frequency control. ELMPC can handle the non-linearity in the system better than PI controllers. ELMPC performs local linearization of the microgrid at each sampling instant and generates the manipulated control trajectory to optimize its future behavior. It performs better than the linear controllers designed based on linearization around a single operating point. At the same time it reduces the computational complexities involved in the non-linear MPC design. Performance of ELMPC is explained through simulation analysis carried out in MATLAB on an eight bus micro-grid.*

Keywords: - Frequency control; isolated micro-grid; linearization; model predictive controller; voltage control.

1. INTRODUCTION

In an isolated micro-grid every DG unit should participate in frequency and voltage control to ensure better transient performance [1]. For this specific reason each DG unit is provided with primary control reserves [2]. PI controller is the most widely used controller for micro-grid control. In synchronous generator based distributed generator (SG-DG), PI controller is employed in the form of governor droop and automatic generation control for frequency control. Excitation system controls the voltage. Control of an electronically interfaced DG unit (EI-DG) with a renewable energy source on DC side involves power sharing control and output control. Power sharing control generates the references for active ad reactive powers based on P-f and Q-V droops. Output control consists of inner current control loop and outer voltage control loop both employing two PI controllers each [3].

However PI controller is not an optimal controller and needs tuning at every operating point of the system to ensure stability and better transient response. It cannot handle the non-linearity in the system properly. For these reasons attention turns towards model predictive controllers (MPC) which are advanced class of controls that can be operated at both centralized and decentralized levels of control architecture. Model predictive controller estimates future output trajectory of a system with the help of mathematical model of the system and its present state information and generates a future control trajectory that optimizes the future response of the system [4]. Then it employs receding horizon principle, where it applies inputs to the system that corresponds to present sample in the entire control trajectory and neglects rest of the trajectory. For the next sampling instant the whole process of future output estimation, generation of optimal control trajectory and application of receding horizon principle is repeated.

When it comes to micro-grid control, most of the literatures employed non-linear MPC [5-6]. When a non-linear MPC is designed for micro-grid control using non-linear micro-grid model, it involves heavy computational burden in generating the optimal control trajectory and is very time consuming. Also the equations corresponding to output estimation becomes very complex. At the same time if we employ linear model predictive controller using a linear approximated model of micro-grid around a single equilibrium point [9], then there is a possibility that the controller performance becomes either unsuitable or unsatisfactory if the load disturbance in micro-grid pushes its dynamics away from the location about which the linearization is valid.

This paper focuses on application of extended linear model predictive controller *(*ELMPC) for micro-grid control which is based on linearization of micro-grid model at each sampling instant. It is intended to provide the controller with low sensitivity with respect to changes in the micro-grid operating point, preserving micro-grid non linearity to the maximum possible extent during controller design [11].

2. SYSTEM DESIGN AND MODELING

An eight bus standalone micro-grid shown in Fig.1 is considered for the study. Rating of generators at buses B1 and B3 are 5 MVA and 2.5 MVA respectively.

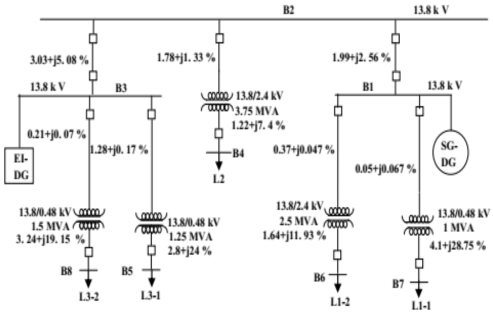

Fig.1. System model (Single line diagram of micro-grid)

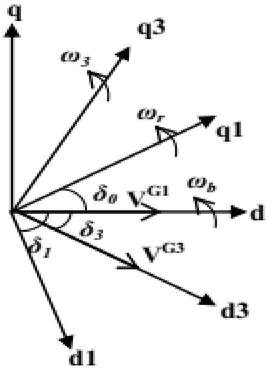

Fig.2. References

Loads L1eq and L3eq in below figure consist of both impedance load and induction motor load.

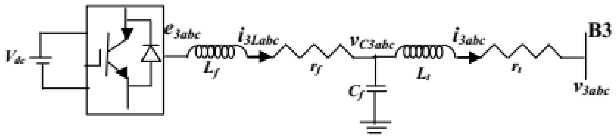

Fig.3.EI_DG Equivalent

Impedance load. At any bus „i", p.u dynamic model of impedance load in global d-q frame is given by:

$$\frac{1}{\omega_b}\frac{dI_{dli,G}}{dt} = -\frac{R_{li}}{X_{li}} I_{dli,G} + I_{qli,G} + \frac{1}{X_{li}} V_{di,G}$$

$$\frac{1}{\omega_b}\frac{dI_{qli,G}}{dt} = -\frac{R_{li}}{X_{li}} I_{qli,G} - I_{dli,G} + \frac{1}{X_{li}} V_{qi,G}$$

Where $I_{dli,G}$, $I_{qli,G}$ are d-q components of ith bus load current. R_{li}, X_{li} are p.u load resistance and inductance at ith bus. $V_{di,G}$, $V_{qi,G}$ are d-q components of ith bus voltage. 5th order dynamic model is used to represent induction motor at ith in P.U

3. PROPOSED SYSTEM AND EXPLANATION

The micro-grid non-linear model is linearly approximated at time t=ts and is written in the form of:

$$\frac{dx_c}{dt} = \bar{X} + A_t x_c + B_t u_t$$

$$y = \bar{Y} + C_t x_c$$

Where X $_c$, u, y are state vector, input vector and output vector. Let n, q, m1 represent number of states, inputs and outputs of the micro-grid. A_t, B_t, C_t represent continuous time state matrix, input matrix and output matrix of micro-grid state space model at time t. Linearization around a non-stationary point results in constant vectors X, Y.
Continuous time model is converted to a discrete model of the form:

$$z_c(k+1) = \bar{Z} + A_d z_c(k) + B_d u(k)$$

$$y(k) = \bar{Y} + C_d z_c(k)$$

(A_d, B_d, C_d) is discrete time state space triplet with {k=0 t=t $_s$}. $\bar{z}$,$\bar{y}$ are discrete counter parts to Z , Y . The discrete model (28) is not suitable for the design of MPC in microgrid scenario as micro-grid control requires an integral action. Hence in order to obtain an integral action, integrators are added to (28) by converting it to an augmented model given by:

$$z(k+1) = \bar{\theta} + A z(k) + B \Delta u(k)$$

$$y(k) = \bar{Y} + C z(k)$$

The new state space representation of triplet is

$$A = \begin{bmatrix} A_d & B_d \\ 0_{q\times 1} & I_{q\times q} \end{bmatrix}, B = \begin{bmatrix} B_d \\ 0_{q\times q} \end{bmatrix}, C = \begin{bmatrix} C_d & 0_{m_1\times q} \end{bmatrix}$$

Let Y_E, U be two vectors that contains estimated outputs and future control trajectory from the present sampling instant respectively. In the present study, control and prediction horizons are considered to be of equal lengths (Np=Nc). Then YE, U are given by:

$$Y_E = \left[y(k_i+1)^T \quad y(k_i+2)^T \ \ldots\ldots\ldots\ldots\ldots y(k_i+N_p)^T \right]^T$$

$$U = \left[\Delta u(k_i)^T \quad \Delta u(k_i+1)^T \ \ldots\ldots\ldots\ldots\ldots \Delta u(k_i+N_p-1)^T \right]^T$$

Finally we can get

$$F_j = \left[CA_{j,1}B \;\; CA_{j,2}B......CA_{j,N_p}B \right], \quad A_{j,l} = \begin{cases} A^{j-l} & \text{if } j \geq l \\ 0 & \text{if } j < l \end{cases}$$

Objective function is given by:

$$J = \min_{U} \left(W - Y_E\right)^T \left(W - Y_E\right) + U^T R U$$

By using this Objective function performance can be calculated. W is the output set point vector for the entire prediction horizon that contains reference values for each element in Y_E. R is the penalty vector that contains penalty on each input in the control trajectory U. Once the optimal control trajectory U is found from, receding horizon principle is applied in which input corresponding to present sampling instant in U i.e. Δu(ki) is considered and rest of the control trajectory is neglected. When the next sample arrives the whole process represented by equations is repeated.

A. INTRODUCTION TO MPC

A block diagram of a model predictive control system is shown in Fig.

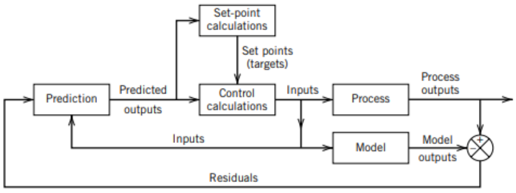

Fig.4. Block diagram for model predictive control.

A process model is used to predict the current values of the output variables. The residuals, the differences between the actual and predicted outputs, serve as the feedback signal to a Prediction block. The predictions are used in two types of MPC calculations that are performed at each sampling instant: set-point calculations and control calculations. Inequality constraints on the input and output variables, such as upper and lower limits, can be included in either type of calculation. Note that the MPC configuration is similar to both the internal model control configuration and the Smith predictor configuration because the model acts in parallel with the process and the residual serves as a feedback signal.

$$Y_1 = \left[\hat{y}^T \; \hat{y}^T ... \hat{y}^T\right]^T, Y_2 = \left[C^T \;\; (C + CA)^T .. (C + CA + .. + CA^{N_p - 1})^T \right]^T$$

$$Y_3 = \left[(CA)^T \;\; (CA^2)^T ......(CA^{N_p})^T \right]^T, Y_4 = \left[F_1^T \; F_2^T .....F_{N_p}^T \right]^T,$$

B. LINEAR MPC

While many real processes are not linear, they can often be considered to be approximately linear over a small operating range. Linear MPC approaches are used in the majority of applications with the feedback mechanism of the MPC compensating for prediction errors due to structural mismatch between the model and the process.

4. SIMULATION DIAGRAM

Fig.5 and Fig.6 shows the simulation diagram of microgrid using ELMPC.

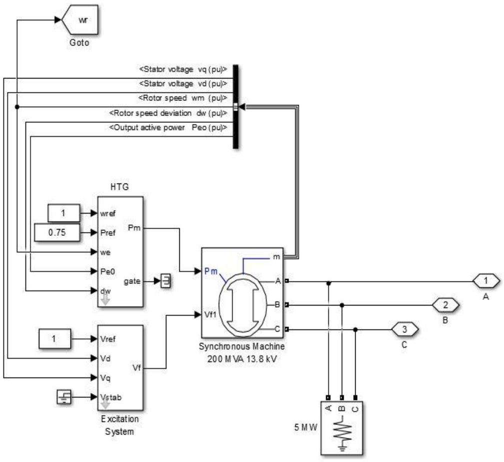

Fig.5.SG-DG Model

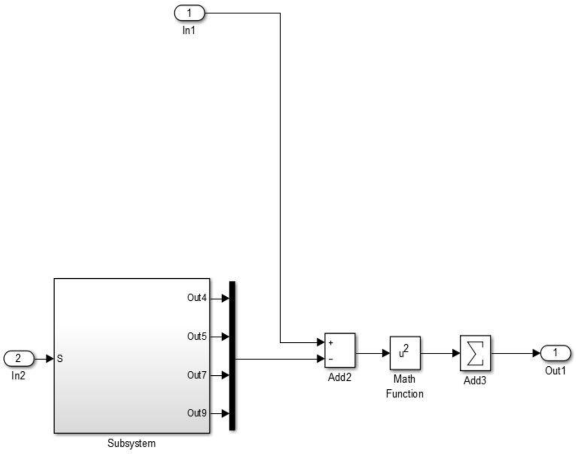

Fig.6. Subsystem

5. RESULTS

Fig.7.a) shows the rotor speed of SG-DG. Due to sudden increase in load (parallel load) the rotor speed drops to maintain the power balance in the micro-grid using its inertia. The rotor speed drops to a minimum of 376.7797 rad/s which is equivalent to 59.9422 Hz. Rotor speed exhibits very slow dynamics when compared to other dynamics in the micro-grid. Rotor speed is restored to nominal value of 377 rad/s in 1.1s approximately.

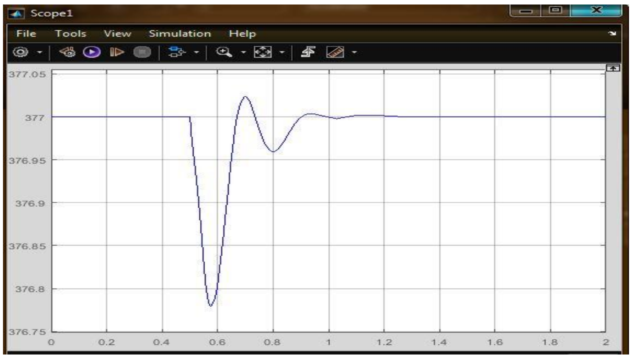

Fig.7.a) SG-DG rotor speed

Fig.7.b) shows the voltage at bus B1. Local reactive power injected by SG-DG restores the voltage to nominal value. The amount of reactive power injection at bus B1 is controlled by the ELMPC through the input signal ΔVin. Voltage at B1 is deviated to a minimum of 0.9717 p.u and is restored to nominal value in 0.1629s.

Fig.7.c) shows the voltage at bus B3. Since the load disturbance happened at bus B3, voltage deviation is more at that bus. It is deviated to a minimum of 0.9532 p.u and restored to nominal value in 0.3348s. Voltage restoration at bus B3 depends on reactive power injected by EI-DG at B3.

Fig.7.b) Voltage at bus B1

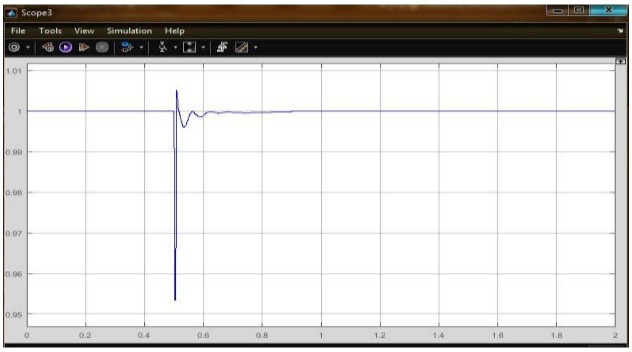

Fig.7.c) Voltage at bus B3

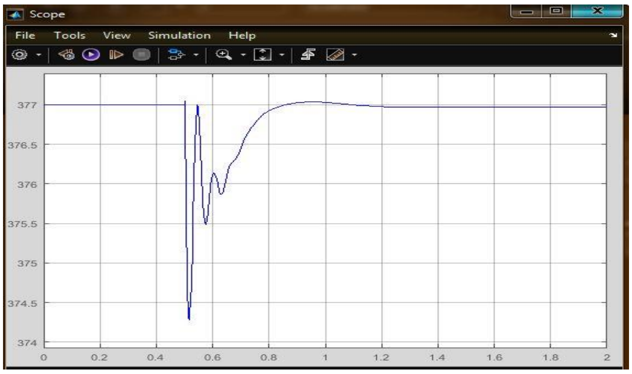

Fig.7.d) Angular speed of d3-q3 frame

Fig.7.e) EI-DG and SG-DG outputs

Fig.7.d) shows the angular speed of d3-q3 frame in rad/s. It is estimated through PLL. Its estimation depends on PI controller parameters of PLL.

Fig.7.e) shows the EI-DG output and SG-DG output. From Fig.7.e) we can observe that during transients EI-DG follows droop characteristics according to angular speed of d3-q3 frame and hence participates in frequency regulation. However in the steady state angular speed of d3-q3 frame returns back to its nominal value of 377 rad/s causing the power output of EI-DG to return back to its pre-disturbance value of 1.5 MW. Hence in the steady state permanent load change is met only by the SG-DG which is evident from the Fig.7.e).

6. CONCLUSION

An extended linear model predictive controller is proposed for micro-grid control in this paper and its performance is evaluated for a sudden impedance load change in MATLAB software. Formulation of control problem and identification of inputs and outputs of the micro-grid are presented in detail. Simulation results show that ELMPC performance is satisfactory. ELMPC is able to coordinate different control signals of different generators in a centralized manner and is able to control the frequency and voltages and is able to make the EIDG participate in frequency regulation during transient state at different buses. ELMPC is successful in implementing EI-DG droop characteristics during disturbances.

The given system has been simulated in MATLAB/Simulink environment.

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