Model Predictive Control Based on System Identification of Photovoltaic Grid Connected Inverter

N. Patcharaprakiti, J. Thongpron, K. Kirtikara, D. Chenvidhya, and A. Sangswang

***Abstract*—This paper proposes a model predictive control of photovoltaic grid-connected inverter based on system identification. The single phase inverter is experimented and its model is determined by using System identification approach with Hammerstein-Wiener model. The derived nonlinear voltage model has accuracy more around 97.34% and it is transformed to the state space model by linearization. A simulation of model based controller uses the discrete time model of inverter to predict the behavior of the output voltage for each possible switching state every sampling time. Then cost function is applied as a criterion for selecting the most suitable switching state for the next sampling interval. The model output is compared with the reference voltage sine wave and the error is feedback to the optimizer. Simulation results shown that the proposed control scheme can achieve the output target with 97% of accuracy.**

***Index Terms*—Model predictive control, system identification, hammerstein – wiener model, grid connected inverter.**

I. Introduction

A grid-connected Inverter is an enabling technology of distributed generator (DG) system to transfer the energy to power system. In particular, inverter control techniques have very important part of power converter to control power quality, efficiency, reliable and safety grid interconnection operation. With this reason, a survey of power inverter control for the grid connection of renewable energy system has been studied [1]. A classical controllers have been developed by linear controller combine with modulation schemes such as voltage oriented control, direct power control, space vector PWM [2]. There are some drawbacks of these methods follow as a mismatch of nonlinear system with linear control, limitation of analog control, computational time of controller [3]. However, by advance technology of computer and digital signal processing, modern techniques have been developed for power converter controlled such fuzzy, neural, adaptive and predictive control. The latter control appears during 80s as an attractive alternative for the control power converter due to its fast dynamic response [4]. The main characteristic of predictive control is use the model of system for prediction of controlled variables and selects the most appropriate control set based on optimality criterion. The classification of model predictive control such as hysteresis based, trajectory based, dead beat controller and model based predictive control are shown in Fig. 1 [5]. Hysteresis based predictive control is controlled system variables between hysteresis bands. The trajectory based is to force the system's variables onto pre-calculated trajectories for example direct self control, direct mean torque control. Some combination of hysteresis and trajectory based strategies likes direct speed control, sliding mode or direct torque control. A well known type of predictive controller use in power converter is dead beat controller. The model is used to calculate the require reference value in order to reach the desired value for certain variable. The modulation was operated by compare the carrier signal to the reference signal. The control gate signal is generated from the many type of modulation.

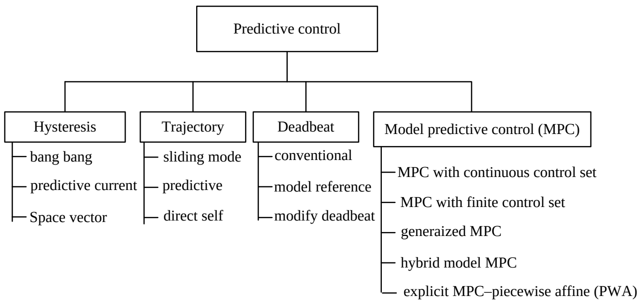

Fig. 1. Classification of predictive control.

The different approach called Model predictive control (MPC) has capable of predicting future output signals based on future input signals and initial values [6]. A model of the system is considered in order to predict the future behavior of the variables over a time period. These predictions are evaluated based on the characteristic of model and cost function, and then the sequence that minimizes the cost function is selected to predict the future control signal. In [7] various kind of MPC is studied such as generalized MPC [8], MPC with nonlinear state space model [9], MPC with continuous control set, MPC with finite control set, hybrid model MPC, explicit MPC [10] and nonlinear MPC [11]. Because of the converter can be modeled as a system with a finite number of switching state, thus a finite control set MPC can be applied for this system [12]. The core of MPC is to create a model for prediction. There are two major approaches for modeling power electronics based system such analytical and experimental approaches. The latter case is suitable for MPC because it will be obtain the model close to the real behavior by use on measured input-output without the prior information. In [13] four linear models and four nonlinear models of grid-connected inverter of PV system

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were compared by system identification process and it was found that Hammerstein-Wiener is appropriated for representation the complex and nonlinear system. There are some applications of MPC based on Hammerstein-Wiener model [14] but it has been not addressed for inverter control application. In this paper, a Hammerstein-Wiener model via system identification approach is performed for model prediction control of PV grid-connected inverter.

II. Model Predictive Control Based on System Identification

In this section, a model predictive control based on system identification approach of inverter is proposed as shown in Fig. 2. The single phase grid-connected inverter convert DC to AC by model based control via power electronics switching schemes. In order to obtain model, the system identification use measured input-output to process the model. The optimizer is calculated the possible switching state by comparison of predicted output or predicted state with reference value. The cost function is used to select the suitable control horizon which generally the gate signals of the inverter that will drive a system output as close as possible to a reference signal.

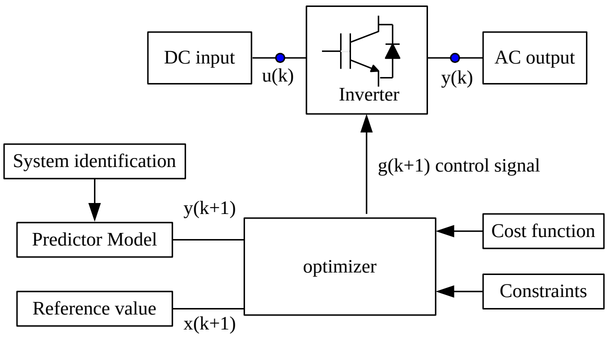

Fig. 2. Model predictive control system diagram.

A. Model predictive control

Model predictive control (MPC) refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of a plant. MPC is based on iterative, finite horizon optimization of a plant model as shown in Fig. 3. The model predicts the future dynamic behaviour of the system over a prediction horizon T_p. At each control interval an MPC algorithm attempts to optimize future plant behaviour by predicting a control horizon T_c. Only the first step of the control strategy from cost function optimization is implemented, then the plant state is sampled again and the calculations are repeated starting from the now current state, yielding a new control and new predicted state path. The prediction horizon keeps being shifted forward and for this reason MPC is also called receding horizon control. Then a receding horizon strategy so that each instant the horizon is moved towards the future which involves the application of the first control signal of the sequence calculated at each step. An optimization cost function of Predictive control is given by without violating constraints in equation (1)

$$J=\sum_{i=1}^{Hp} W_{xi}\left(r_i-x_i\right)^2+\sum_{i=1}^{Hp} W_{ui}\Delta u_i^2 \tag{1}$$

where x_i is i^{th} controlled variable (output voltage), r_i is i^{th} reference variable (reference voltage), u_i is i^{th} manipulated variable (control gate signal), W_{xi} is weighting coefficient reflecting the relative importance of x_i, W_{ui} is weighting coefficient penalizing relative big changes in u_i and H_p is number of receding horizon.

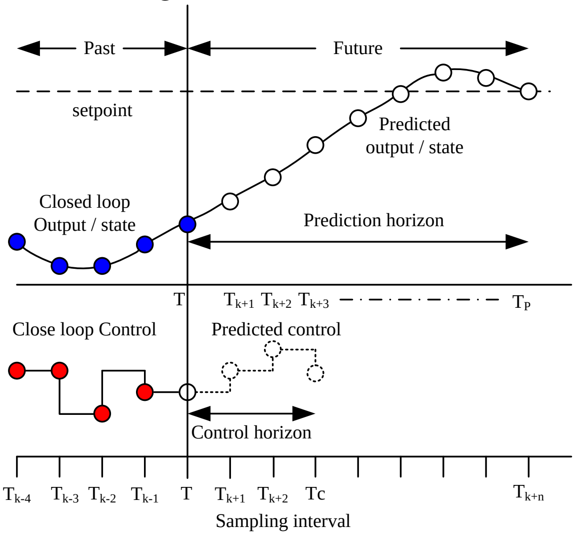

Fig. 3. Principle of model predictive control.

B. System identification based modeling

The core of control is the first is to obtain the model and calculation cost function to derive the control signal. In order to obtain a model, system identification approach based on Hammerstein-Wiener model is applied. A Hammerstein and Wiener model is combining from a Wiener and Hammerstein model, enabling combination of a system, sensors and actuators in one model as shown in Fig. 4.

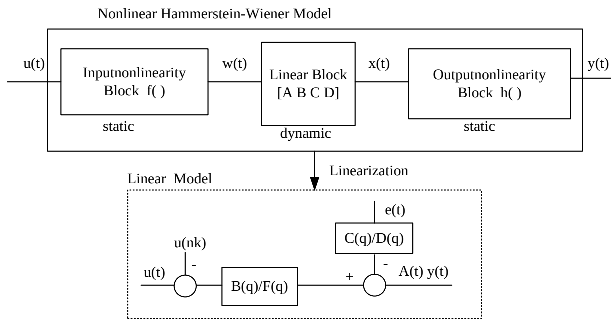

Fig. 4. Structure of hammerstein-weiner model and linear model.

The following general equation describes the Hammerstein-Wiener structure are follow equation (2)

$$\left.\begin{aligned} w(t) &= f(u(t)) \\ x(t) &= \sum_{i}^{nu}\frac{B_i(q)}{F_i(q)}w(t-n_k) \\ y(t) &= h(x(t)) \end{aligned}\right\} \tag{2}$$

which $u(t)$ and $y(t)$ are the inputs and outputs for the system. $w(t)$ and x(t) are internal variables that define the input and output of the linear block. In linear block, there are polynomials B and F contain the time-shift operator q, essentially the z-transform which be expanded as in equation (3). n_u is the total number of inputs. b_n and f_n are input coefficients. n_k is the input delay that characterizes the delay response time and $e(t)$ is the error signal. The order of the model is the sum of b_n and f_n. This should be minimum for the best model. The Hammerstein-Wiener Model compose of the input and output nonlinear block which contain nonlinear functions $f(\bullet)$ and $h(\bullet)$ that corresponding to the input and output nonlinearities. The both nonlinear blocks are implemented using nonlinearity estimators. Inside nonlinear block, nonlinear estimators are composed of deadzone, saturation, piecewise, sigmoidnet and wavenet.

$$\begin{aligned} B(q) &= b_1 + b_2 q^{-1} + \dots\dots + b_n q^{-b_n+1} \\ F(q) &= 1 + f_1 q^{-1} + \dots\dots + f_n q^{-f_n} \end{aligned} \quad (3)$$

The nonlinear system can be linearized by linearizing around a specific operating, then the behaviour of system can be applied for linear system. The Discrete time state space models provide the linear difference relationship between the inputs and the outputs as the linear output-error model as shown in equation (4). This equation is used to predict output or state of system for model predicted control.

$$\begin{aligned} x(t+Ts) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t) \end{aligned} \quad (4)$$

III. Experimental Modeling and Simulation of Control Strategy

In order to control inverter by MPC three procedures is performed which composed of i) grid connected configuration and switching control, ii) inverter modeling by using system identification and iii) controller design such as cost function, constrain, disturbance.

A. Single phase inverter and control topology.

The inverter composed of DC-link, four switched of power electronics such IGBT or MOSFET and output filter and AC link for synchronization to the power system is shown in Fig. 5 and equivalent circuit of each status is transformed in to the circuit are shown in Fig. 6. The equation of single phase inverter is shown in equation (5). The constraint of switching of inverter, in one branch t allow only one switch active and blanking time is used for avoid this situation. There are four possible switching patterns which compose of two active vectors and 2 zero vectors as shown in Table I. In table the number 1 of switch is stand for switch on and 0 is mean switch off.

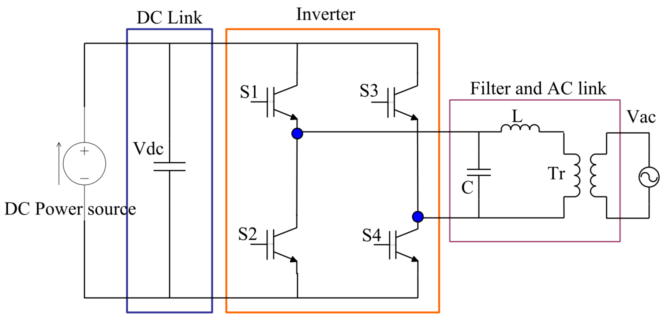

Fig. 5. Configuration of single phase grid-connected inverter.

$$\left.\begin{aligned} \frac{di_{ac}}{dt} &= \frac{R}{L} i_{ac} + \frac{1}{L}(v_{dc} - v_{ac}) \\ v_{ac} &= -Ri_{ac} - L\frac{di_{ac}}{dt} + v_{dc} \end{aligned}\right\} \quad (5)$$

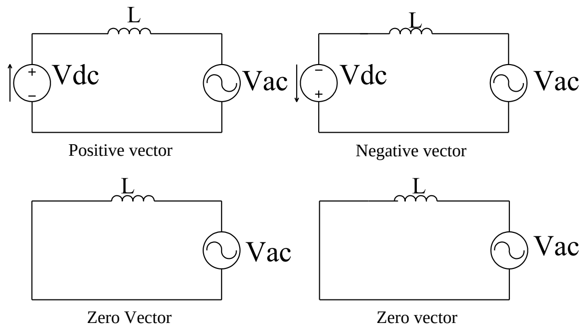

Fig. 6. Equivalent circuit in each state of single phase inverter.

TABLE I: A Switching State of Inverter.

State	S1S2S3S4	Vector State
g1	1001	Active State
g2	0110	Active State
g3	1010	Zero State
g4	0101	Zero State

B. Modeling inverter using System identification

The experimental system composes of DC power supplies, digital power meter, digital oscilloscope, resistive (R), inductance (L) and capacitive (C) load, AC power system and computer. After connect and energize power in inverter, connected load and AC power system, then voltage, current and power wave- forms have been collected by oscilloscope and transmitted to computer in batch processing single input and single output (SISO) type. The system identification process is shown in Fig. 7, the voltage waveform data are divided in two groups follow as estimate data and validate data. Then, the various nonlinear estimators of input and output system have been chosen for estimate the system in represent the nonlinearity behaviour. The developed programming will check accuracy of waveform and find the maximum accuracy waveform compare with real waveform by adjust the pole, zero and delay of the linear terms.

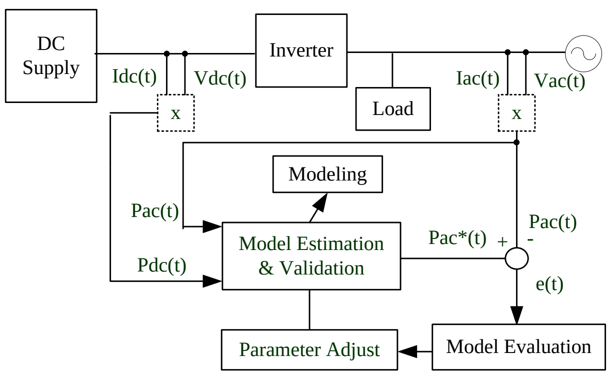

Fig. 7. System identification to obtain inverter model.

C. Model Predictive control Simulation

The model based control algorithm for simulation is shown in Fig. 8 and its iterative operation is described in Fig. 9. The program is started from calculated the prediction state from model. The number of prediction horizon is determined and the possible switching state of each prediction horizon is calculated. The cost function is evaluated with voltage reference and constrain. The next step is the selection the suitable switching state which can control the prediction state as close as the reference value. The simulation of MPC control is performed by prediction horizon and control horizon calculations in every sampling period. The plant model is composed of plant, disturbance and noise. The parameter of controller is designed for control the system as shown in Table II. Finally, the optimized manipulated control switching state is obtained to command the four power electronics switches.

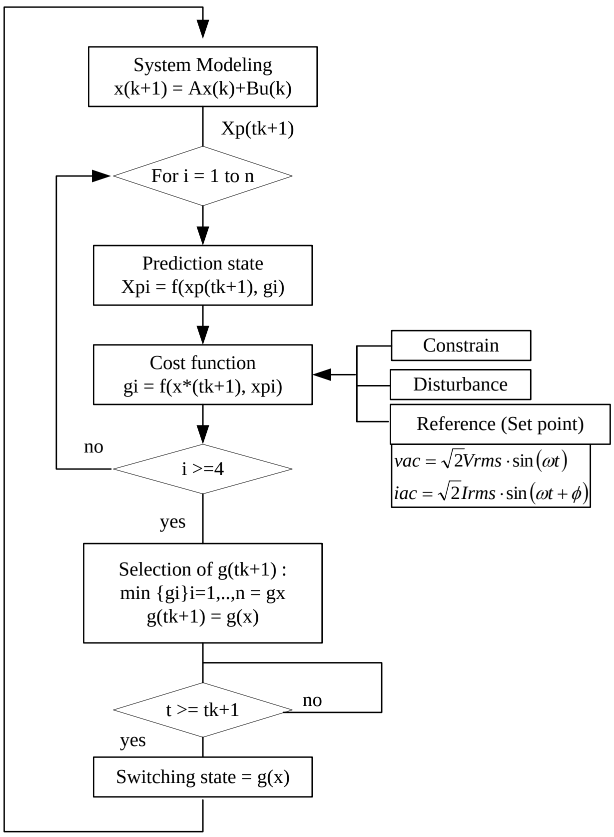

Fig. 8. Model predictive control algorithm.

TABLE II: SIMULATION PARAMETER FOR MODEL PREDICTIVE CONTROL.

No	Parameter	Unit	Value
1	Plant model	-	State space
2	Prediction horaizontal	step	100
3	Control horaizontal	Step	20
4	Input Voltage	V	220
5	Output Voltage	V	$380\sin(\omega t+\phi)$
6	Reference value	V	$380\sin(\omega t+\phi)$
7	Manipulate control		gate signal
8	Constraint	step	Infinity
9	Weight tuning	-	0.8
10	Estimation gain	-	0.5
11	Disturbance	-	Step (magnitude 1.0)
12	Noise	-	White (magnitude 1.0)

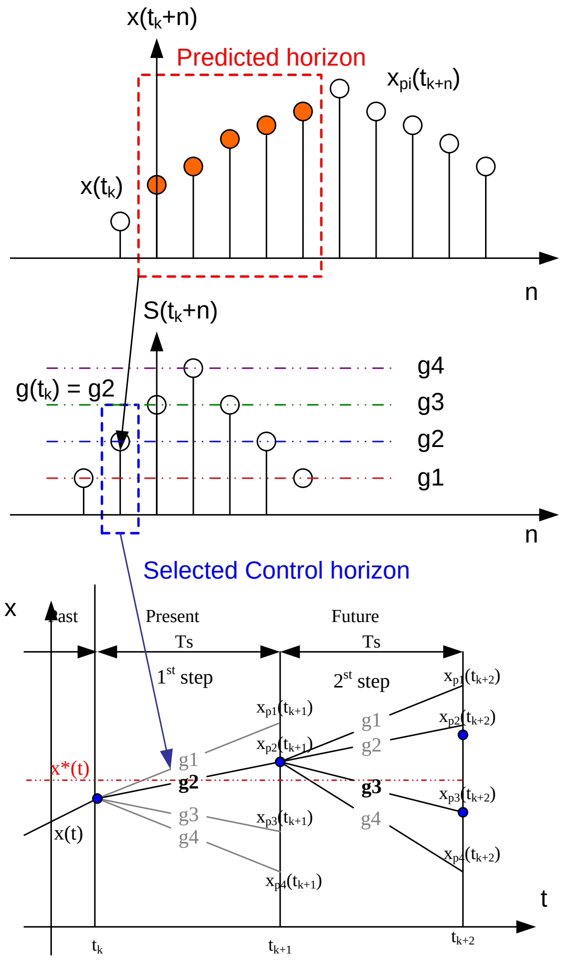

Fig. 9. Model predictive control operating principle.

IV. Result and Discussion

After measurement and estimating data by system identification process, the validation of model is processed. The most suitable model derived by programming. The highest accuracy waveform of output is derived and the smallest order. The model composes of piecewise-linear estimators and linear parameter with pole, zero and delay equal to 4, 5 and 3. The comparison between experimental waveform and model is equal to 97.73% as shown in Fig. 10. The model is used to predicted the output voltage for generate control horizon from MPC algorithm. The simulation output voltage of model prediction control and reference voltage is compared as shown in Fig. 11. The simulation result is demonstrated that MPC can control the output waveform close to the reference voltage approximately 97%.

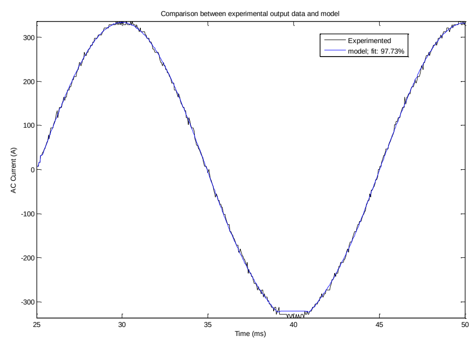

Fig. 10. Comparison between modeling output and experimental waveform.

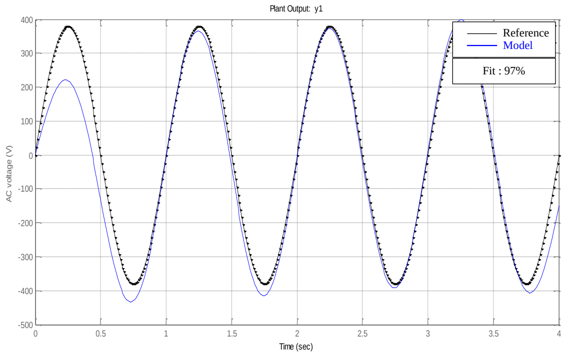

Fig. 11. Comparison between output reference and predicted output.

V. Conclusion

In this paper, the model prediction control of photovoltaic grid-connected inverter is studied. The model used in MPC is derived from system identification approach based on nonlinear Hammerstein-Wiener model. The system identification is performed by input-output waveform measurement, estimating data, the validation of model and adjusts the system parameter by programming. The simulation of model predicted control is performed by transformed model into state space equation for generate predicts output. The model output is compared with reference voltage and finds the possible switching state. Finally, an optimal switching state is obtained by constrain and cost function. The simulation result shown that output voltage is closely to the reference voltage.

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