Chapter

Model Reference Adaptive Control of Solar Photovoltaic Systems: Application to a Water Desalination System

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Abstract

The major problem of the industrial sectors is to efficiently supply their energy requirement. Renewable energy sources, in particular solar energy, are intermittently accessible widely around the world. Photovoltaics (PV) technology converts sunlight to electricity. In this work, we present a contribution dealing with a new mathematic development of tracking control technique based on Variable Structure Model Reference Adaptive Following (VSMRAF) control applied to systems coupled with solar sources. This control technique requires the system to follow a reference model (the solar radiation model) by adjusting its dynamic and ensuring the minimal value of error between the plant dynamics and that of the reference solar radiation model. This chapter provides a new theoretical analysis validated by simulation and experimental results to assure optimum operating conditions for solar photovoltaic systems.

Keywords: optimization, solar energy applications, following control, photovoltaic, reference model-forecasting

1. Introduction

Using solar energy in several applications becomes more and more interesting in order to minimize the cost of production for any system coupled with solar photovoltaic energy. In particular, water desalination systems, which we are going to mention in this book chapter, actually require renewable energy sources to minimize the cost of producing huge amounts of needed water.

Solar energy is only available during daylight hours. Furthermore, problems of intermittent natural solar energies are rarely discussed in practical use cases as power fluctuates over time. Thus, we must introduce real-time operating procedures.

In addition, sunrise and sunset cause daily fluctuations, so the energy delivered by panels will not be constant and it can also suddenly vary due to clouds. Thus, there is a risk of not supplying the energy demand of the load. As an example, when the load consists of a water desalination system, the minimum of sunshine variation can provoke the clogging of membranes used for reverse osmosis desalination, which causes the destroying of the whole desalination system.

The production of needed water in large quantities demands excessive consumption of energy. Thus, we need to reduce the cost of water production to the maximum possible. Many studies have been carried out to link renewable energy with water production [1, 2]. Furthermore, process control is an important part of the coupling of solar energy to industrial systems; in particular, the desalination industry requires to be operated at the optimum conditions. When coupled to solar photovoltaic sources [3], all industrial systems must be equipped with a regulation energy system to guarantee a continuous energy supply.

The intermittence of solar energy provokes an unstable electrical supply of the photovoltaic solar plants, so the industrial system's parameters change their values with time in an unknown range.

The main idea is to develop a control strategy based on following control theory in order to force the industrial system to adapt to variations in solar photovoltaic energy.

Hence, our idea is to combine two types of robust controls: the adaptive control characterized by its real-time adjustment and the sliding mode control, characterized by its robustness [4–9]. Many formulae have been derived to tune the variable Structure Model Reference Adaptive Following control [10].

To guarantee the stability of the photovoltaic system in the opposite of the intermittence of sunshine, we have chosen a new control algorithm designed by VSMRAF judges effective against stochastic disturbances of uncertainties. These uncertainties affecting the dynamic of photovoltaic solar sources come from various sources [11]. Essentially, they are due to the following reasons: solar sources modeling, intermittent sunshine, solar systems position, approximations in dynamic models. Consequently, all these parameters must be taken into account in the development of photovoltaic solar sources control laws in order to optimize their operation and to avoid all the storage disturbances that may take place and affect the performance of the solar-photovoltaic source.

To overcome renewable energy variability, many strategies were proposed such as:

The application of Maximum Power Point tracking (MPPT) has different algorithms. This method requires high-performance control and seems to be heavy in experiment plants adding to high dependency on specialized and accurate sensors (voltage and current sensors) [12].

The theory of Large Law Number (LLN) can be applied in the use of many solar sources to assure the stability of the electric energy offered by the solar source. Obviously, this solution is expensive at the level of the installation of the solar system.

The use of hybrid renewable systems, for example, wind-solar systems is also proposed as a solution to overcome the problem of solar intermittency. Although this technique is practically possible, the geographical diversity of locations represents a real challenge among many other enormous challenges for this solution.

In other literature [13, 14], we proposed several methods of prediction of solar energy and how much it can be available a day. This theory seems to be not practical and extremely difficult since there are several parameters involved in the prediction algorithms.

In this book chapter, we propose a novel technique depending on a dynamic model of the system itself and taking into account the uncertainties introduced by the intermittence of the photovoltaic solar source. This technique reinforces the robustness and the stability of the system with respect to the disturbances caused by the variation of the solar source.

This book chapter is organized as follows: a state of the art has been presented in the introduction to explore the literature and the research developed to solve the problem of solar energy variation and its effect on industrial systems coupled to photovoltaic sources.

The second section is devoted to the material and methods section. We have presented theoretical elements and mathematic development of the VSMRAF control algorithm. This algorithm is applied to an uncertain dynamic model of the system coupled to a photovoltaic solar source. During the coupling of this system to the photovoltaic solar energy, this model will allow us to avoid the disturbances due to the variation of the electric power supply during the intermittence of the solar energy. We have also presented a background on photovoltaic solar sources and the description of our experimental study plant, which consists of a Reverse Osmosis Desalination (ROD) system coupled to a photovoltaic solar source (PV-ROD) system.

The last section deals with the main simulated and experimental results obtained by our experimental plant relating to a real example of coupling a water desalination system to a solar photovoltaic system.

In conclusion section, we have summarized the main results of this book chapter and we have presented the main findings as well as the perspectives of this research work.

2. Material and methods

2.1 Theoretical elements

2.1.1 Multi input multi output linear uncertain systems

The following model represents the state-space model of an uncertain system [15–18].

The pair of matrices (ΔA, ΔB) represents the incertitude affecting the state matrix A and the control matrix B of the linear system.

$$\dot{x} = (A + \Delta A)x + (B + \Delta B)u \tag{1}$$

The uncertainty state matrices of the system correspond to Eq. (1).
where

$$[\Delta A \ \ \Delta B] = D_1 \nabla [E_1 \quad E_2] \tag{2}$$

$D_1 \in \Re^{nxd}$ $E_1 \in \Re^{exn}$ $E_2 \in \Re^{exm}$
The uncertain matrices ΔA and ΔB are bounded in norm.

2.1.2 Novel mathematic development for the following control strategy

In this approach, we will develop the mathematical formulations detailed in [19] concerning the structure of the adaptive sliding mode control of multivariate systems by tracking a reference model, by replacing the multivariate system represented in the state space by Eq. (3).

$$\dot{x} = Ax + Bu \tag{3}$$

If we replace A and B with their novel expressions taking into account the uncertain matrices, we find the Eq. (4).

$$\dot{x} = (A + \Delta A)x + (B + \Delta B)u \tag{4}$$

Our following theorem shows that if we select a reference model, we can neglect the incertitude on ΔB matrix.

2.1.3 Ben Chaabene's theorem

As we have developed in [19], the reference trajectory in the state space $\boldsymbol{Cr}$ is independent of the effect of uncertainties on the system's dynamic. To take into account the uncertainties on the system, we have assimilated its trajectory in the state space to a cylindrical envelope ($\boldsymbol{E_s}$) with a radius r depending on uncertain matrix $\boldsymbol{\Delta A}$. This matrix depends on the following error and represents the possible deviation of the system evolved from its reference trajectory. As in the VSMRAF control, the reference matrix of control $\boldsymbol{B_r}$ has constant values, so $\boldsymbol{B_r} = \boldsymbol{B}$, and consequently $\boldsymbol{\Delta B} = \boldsymbol{0}$.

The trajectory can be represented by **Figure 1**.

Consider the state representation of an uncertain system and from the theorem and the Eq. (4), we find that:

$$\dot{x} = (A + \Delta A)x + Bu \tag{5}$$

The state-space reference model is represented by the following equation.

$$\dot{x}_r = A_r x_r + B_r u_r \tag{6}$$

Two matrices $\boldsymbol{\theta^*}$ and $\boldsymbol{Q^*}$ are defined in order to determine the reference model matrices $\boldsymbol{A_r}$ and $\boldsymbol{B_r}$:

$$A_r = A + \Delta A + B\theta^* \tag{7}$$

$$B_r = BQ^* \tag{8}$$

With:

$\boldsymbol{\theta^*}$: matrix with dimension (m × n).

$\boldsymbol{Q^*}$: diagonal matrix (m × m).

The control law stretching the error to zero is defined.

$$u = \psi x + Q^* u_r \tag{9}$$

The matrix $\boldsymbol{\Psi}$ is an against-reaction matrix of dimension (m × n). The switching functions $\boldsymbol{\Psi_{ij}}$ of the matrix $\boldsymbol{\Psi}$ are adjusted by a variable structure approach. The tracking error $\boldsymbol{x_{ei}}$ for the uncertain system is determined as follows:

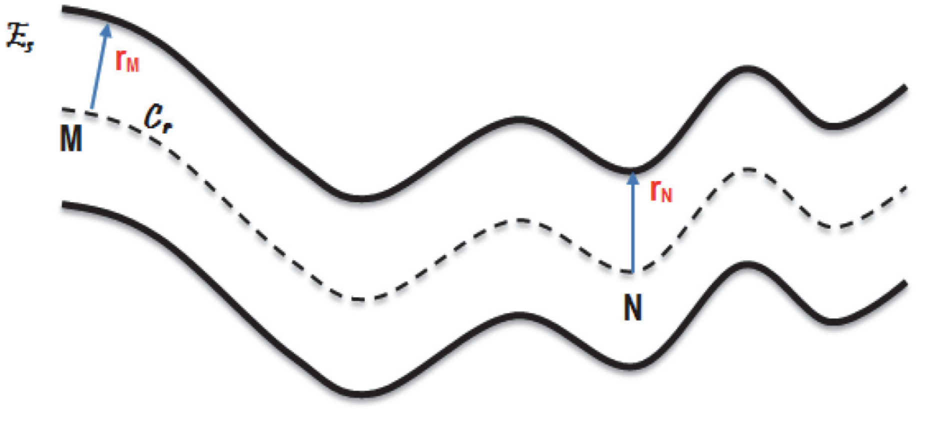

Figure 1.
Effect of the uncertainties on the evolution of the continuation error.

$$x_{ei} = x - x_r \tag{10}$$

If we derive the Eq. (10) with respect to time we find.

$$\dot{x}_{ei} = \dot{x}_i - \dot{x}_{rm} \tag{11}$$

By replacing $\dot{x}$ and $\dot{x}_r$ by their expressions in Eqs. (5) and (6), we obtain:

$$\dot{x}_{ei} = (A + \Delta A)x + Bu - (A_r x_r + B_r u_r) \tag{12}$$

The Eq. (7) gives:

$$A = A_r - \Delta A - B\theta^* \tag{13}$$

Consequently.

$$\dot{x}_{ei} = (A_r - B\theta^*)x + Bu - A_r X_r - B_r u_r \tag{14}$$

By replacing the control law with its expression in Eq. (9) and using the Eq. (14), we obtain:

$$\dot{x}_{ei} = A_r(x - x_r) + B(\psi - \theta^*)x \tag{15}$$

By comparing the Eq. (15) to expressions in literature such as detailed in Eq. (14) for the certain systems (or systems without uncertainties), we find that the derivative of the state error for the uncertain system has the same expression than the following Eq. (16).

$$\frac{\boldsymbol{de}}{\boldsymbol{dt}} = \boldsymbol{A_r e} + \mathrm{B}(\psi - \theta^*)\mathrm{X} \tag{16}$$

Consequently, the VSMRAF technique allowed us to eliminate the affection of the system dynamic by uncertainties due to sunshine intermittence.

2.2 Application to water desalination system fed by photovoltaic solar source

2.2.1 Design of the experimental plant

The experimental plant that we have used to validate theoretical results is shown in **Figure 2**. It is essentially composed by 3 principal parts:

- A Photovoltaic (PV) system
- High Pressure (HP) pump
- A reverse osmosis desalination (ROD) unit

The brackish or sea water is pumped into a closed vessel and pressurized to the RO unit by a High Pressure (HP) pump, which is fed by the photovoltaic solar source using solar panels. The RO unit is a semi-permeable polyamide membrane, composed of two sides: a brine side and a permeate side. Saltwater is pumped back to the membrane where the salt solution is rejected by the brine side and the desalted pure water passes through the permeate side.

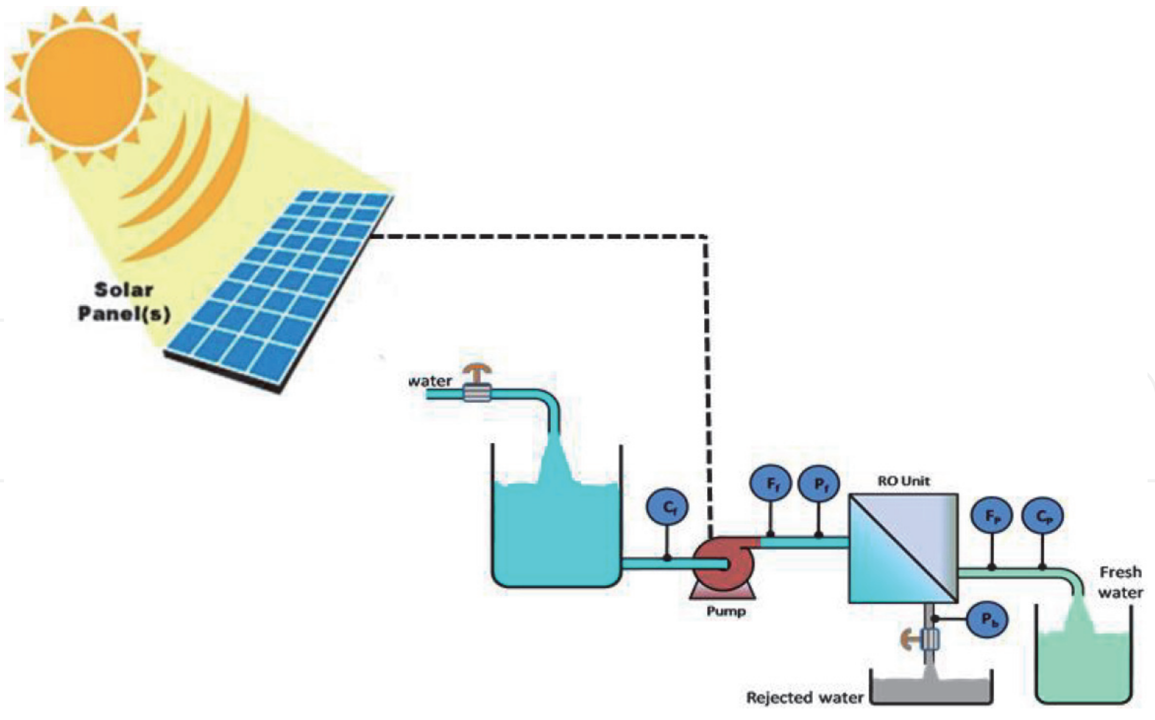

Figure 2.
Design of the photovoltaic reverse osmosis water desalination system.

2.2.2 The photovoltaic system

Solar PV systems are composed of the following components [20]:

- PV arrays consisting of a number of PV modules or panels wired in parallel and/or series association to provide desired voltage and current. Each PV module is composed of many PV cells associated in series to produce high voltages and in parallel to increase current intensity.

  Solar cells are semiconductors made from silicon (single or polycrystalline) devices that convert sunlight into direct current (DC). **Figure 3** shows the equivalent electric circuit of the PV solar cell [21] with all parameters designed in the abbreviations table.

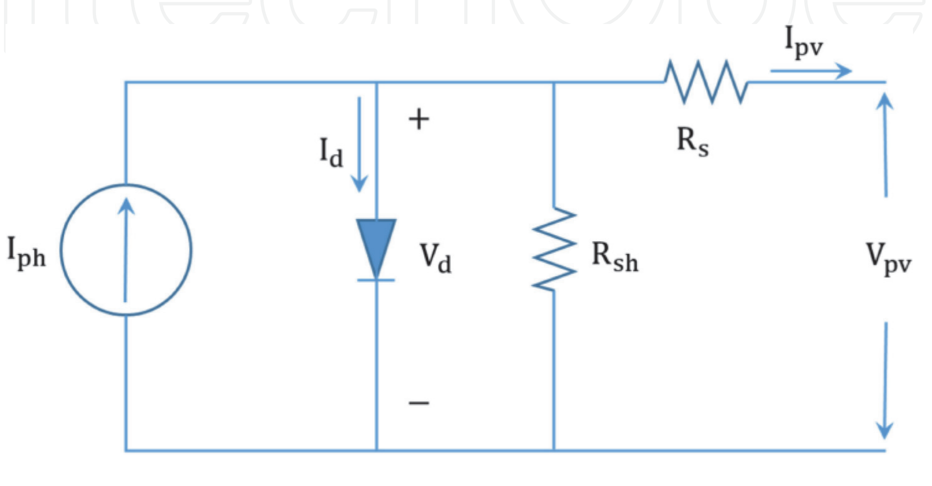

Figure 3.
The equivalent electric circuit of the photovoltaic solar cell.

- Solar inverter, which transforms direct current produced by PV modules to alternative current (AC) needed by AC loads.

- A bias of system (BoS), the generation of AC and DC power.

- Batteries were used in case of off-grid PV systems or when power is needed at night.

Mathematic laws of the PV solar cell model are given by the following expressions detailed in [15].

$$V_D = V_P + R_S I_P \tag{17}$$

$$I_P = I_{ph} - I_D - (V_D/R_{sh}) \tag{18}$$

$$I_P = I_{ph} - I_s\left[\exp\left(qV_D/AKT\right) - 1\right] - V_D/R_{sh} \tag{19}$$

2.2.3 Description of our photovoltaic system

Figure 4 shows a PV (crystalline silicon) system with 42 kwp capacity, installed at the Research Center of Energy Technologies (CRTEn) in the Borj Cedria techno pole in the south of Tunis.

The installed PV system consists of three PV arrays including 172 modules (64 each one) and 3 inverters with capacity of 17.5 kVA each one. **Table 1** gives the characteristics of one PV module.

2.2.4 Experimental plant

The whole reverse osmosis (RO) desalination system used as an experimental plant is shown as follows. This system contains essentially 3 RO modules, a Moto pump, and an electronic card for data acquisition from various sensors already installed. This system is coupled to a photovoltaic system.

Figure 4.
The photograph of the PV system installed at CRTEn Borj cedria in the south of Tunis.

Characteristics	Units	STC conditions
Maximum power P_{max}	W	250
Voltage at P_{max}	V	28.90
Current at P_{max}	A	8.66
Open circuit voltage	V	37.60
Short circuit current	A	9.29

The total amount of energy produced annually by the PV system is 94.124 MWh/year.

Table 1.
PV module electrical characteristics.

3. Simulation and experimental results

3.1 Desalination system state-space model

The simulation of the Reverse Osmosis Desalination system dynamic was effected Using Matlab software. The state-space model of the system is given by Eq. (5). The following constant matrices ***A, B,*** and ***C*** are determined from experimental results.

$$A = \begin{pmatrix} -1 & 1 & 0 & 0 \\ -2.25 & -1.50 & 0 & 0 \\ 0 & 0 & -1 & 1 \\ 0 & 0 & -4.62 & -3.23 \end{pmatrix} B = \begin{pmatrix} 2.50 & 0 \\ 0 & -0.56 \\ 0 & -0.20 \\ -0.81 & 0 \end{pmatrix} C = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

$$\Delta A = \begin{pmatrix} 0.09 & 0 & 0 & 0 \\ 0.81 & 0.78 & 0 & 0 \\ 0 & 0 & 0.09 & 0 \\ 0 & 0 & 1.66 & 1.68 \end{pmatrix}$$

As it is shown by the Matlab Simulink model in **Figure 5**, we have replaced all matrices of the state-space model using their real experimental values to test the performances of the following of the model by the system. Values of the uncertain matrix ΔA show that it is bounded in the norm. The real values of the uncertainty matrix show that the deviation of the system from its reference trajectory is limited and offers a margin of robustness to this system during its dynamic evolution.

3.2 VSMRAF control algorithm

Figure 7 shows the chronology of the calculation steps of the VSMRAF control algorithm. After the calculation of the control law, the following error was decreased, then the system was forced to follow its reference model.

Figure 6 shows the PV-RO water desalination experimental set-up used for real experimentations.

Figure 5 shows the PV-RO desalination system diagram using the Matlab Simulink procedure.

3.3 Test of system tracking dynamics

To test the PV-ROD system dynamics, we proceed to impose the reference model and control the real evolution of the system dynamics compared to the

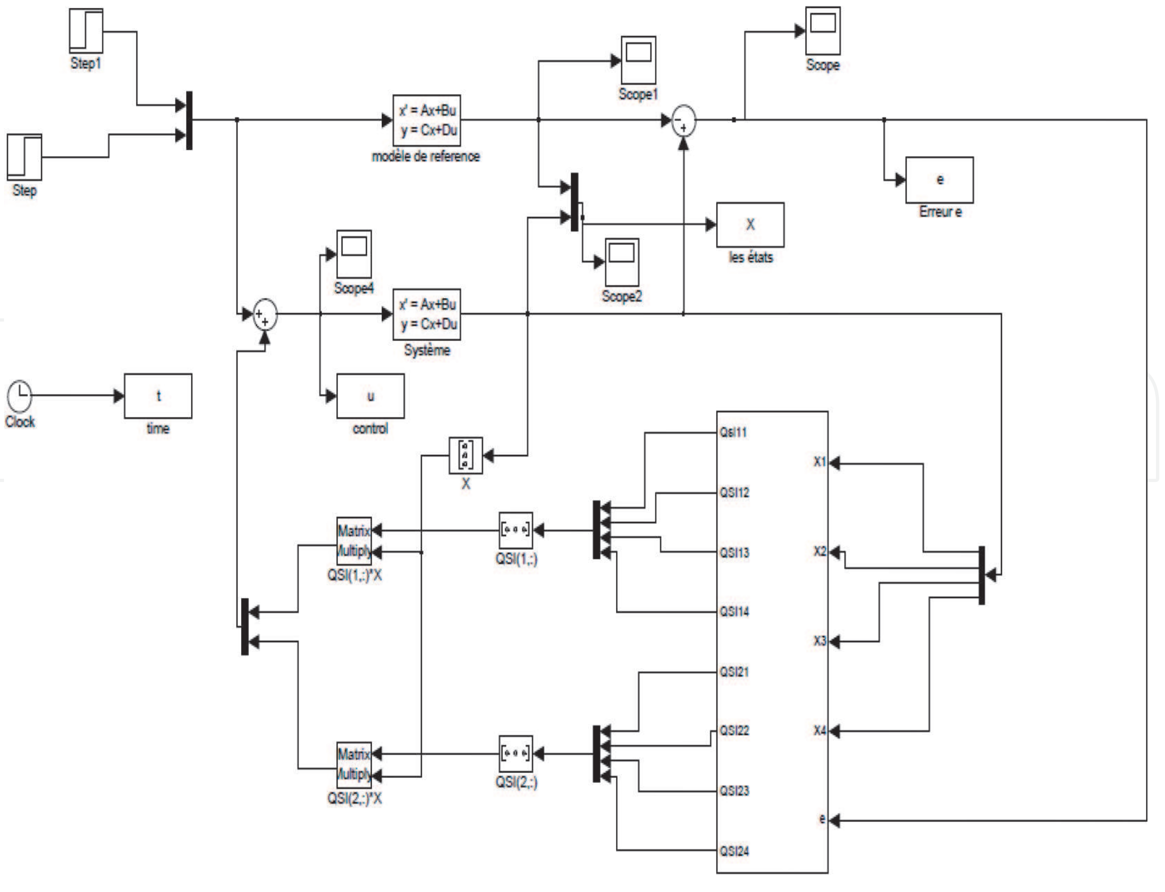

Figure 5.
Matlab Simulink model of the PV-RO desalination system.

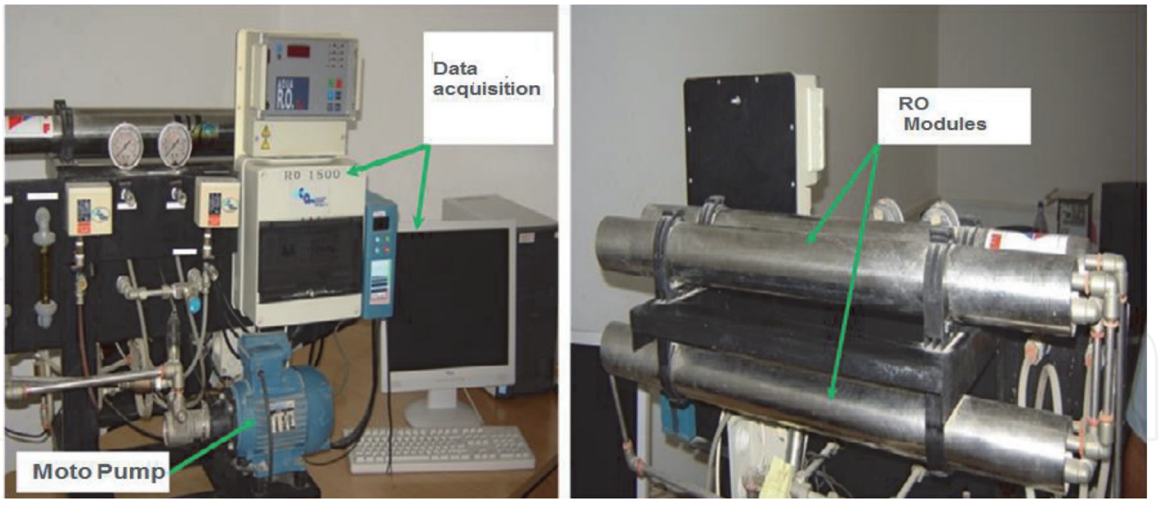

Figure 6.
PV-RO water desalination experimental set-up.

reference model evolution. The following curves show the tracking performance for parametric uncertainties of different values of uncertainties, which correspond to the variations of the photovoltaic solar energy caused by the variation of the sunshine. We note that we have chosen three uncertainty values, which are 10%, 20%, and 40% to follow the tracking performance of the system. The choice of these values of uncertainties stems from the fact that a preliminary study shows that they do not often exceed 25%.

Figures 8 and **9** show respectively, the step responses of the product water flow rate Q and the product salinity Cs for uncertainty of 10%, the reference trajectory is

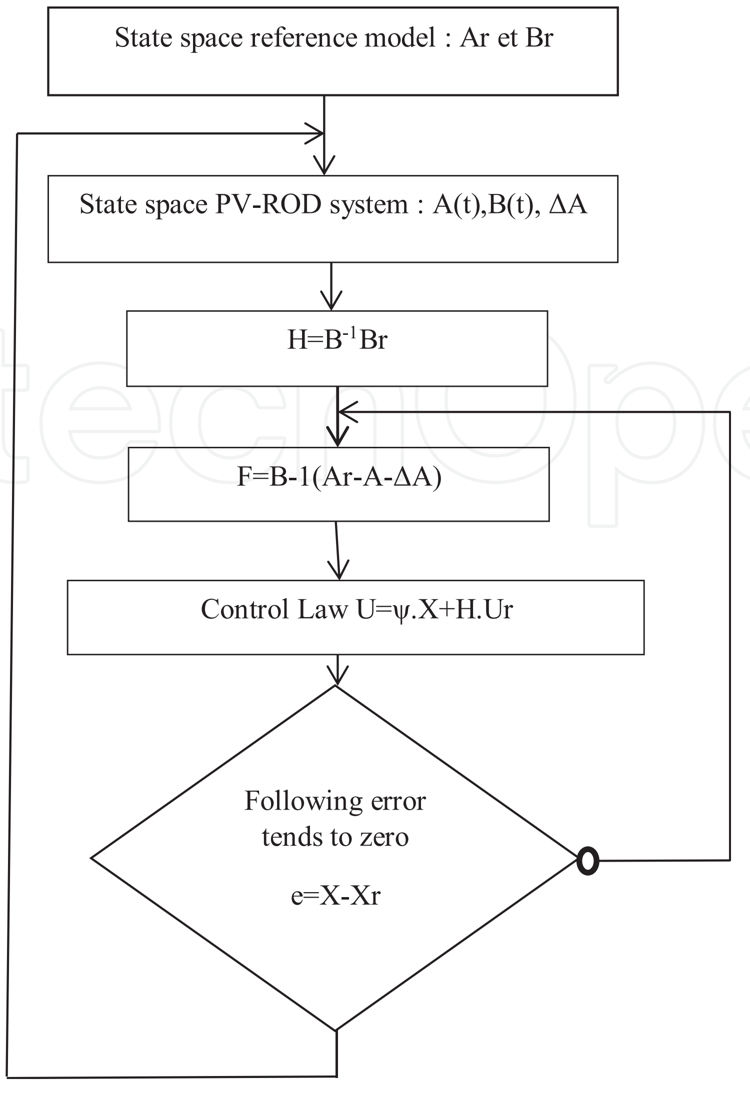

Figure 7.
Algorithm of the VSMRAF control of the PV-ROD system.

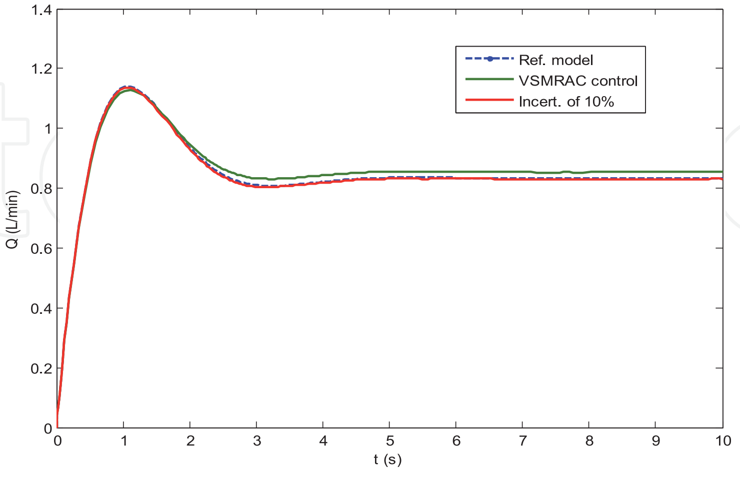

Figure 8.
Flow rate tracking dynamics for uncertainty of 10%.

characterized by a slow dynamic. Curves show perfect model following at a finite time. The tracking error values do not exceed 3% for both of the two outputs Q and Cs.

The evolution of the two parameters Q (flow rate) and Cs (output salinity) is shown in **Figures 10** and **11**. These figures show the perfect following of the model even with an uncertainty of 20%. The tracking error is less than 5%.

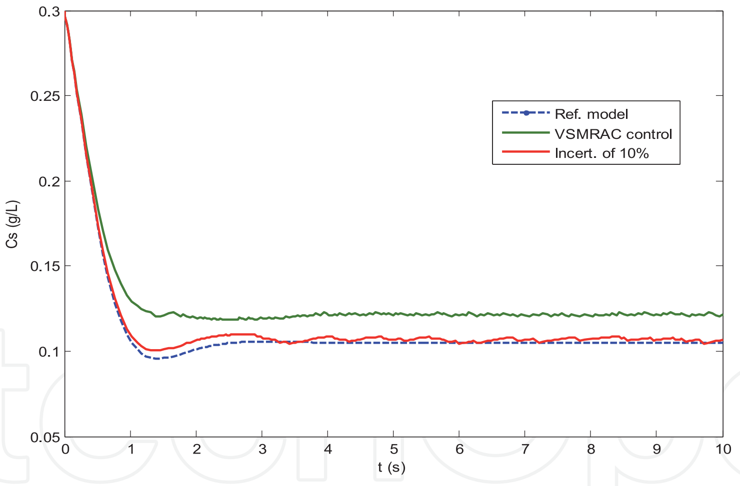

Figure 9.
Salinity tracking dynamics for uncertainty of 10%.

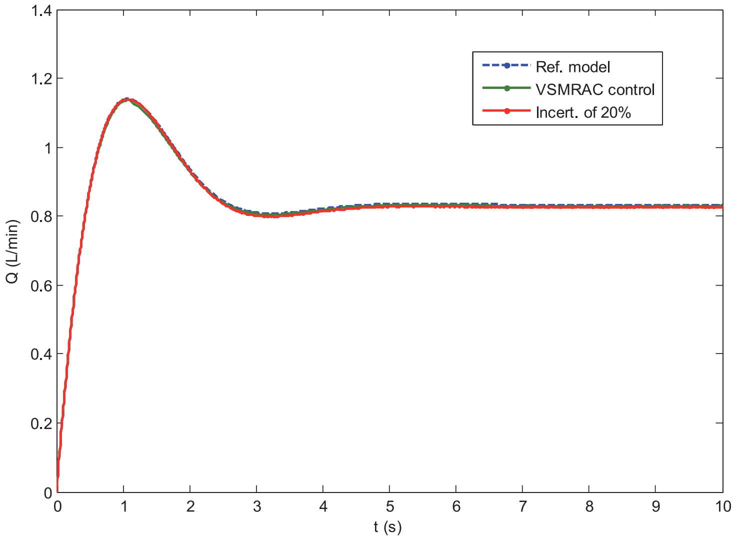

Figure 10.
Flow rate tracking dynamics for uncertainty of 20%.

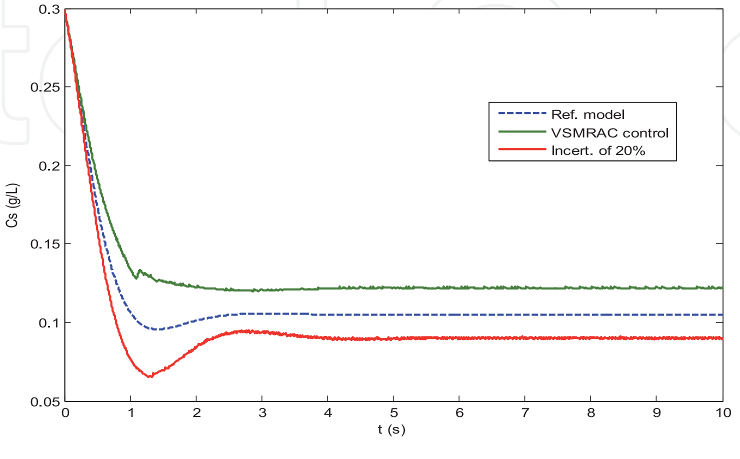

Figure 11.
Salinity tracking dynamics for uncertainty of 20%.

The evolution of the two parameters Q (flow rate) and Cs (output salinity) is shown in **Figures 12** and **13**. These figures show the perfect following of the model even with an uncertainty of 40%. The tracking error is less than 8%.

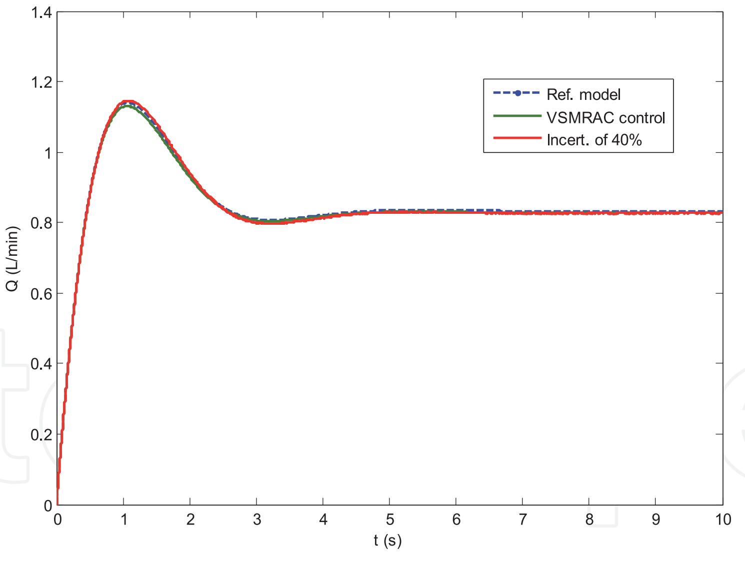

Figure 12.
Flow rate tracking dynamics for uncertainty of 40%.

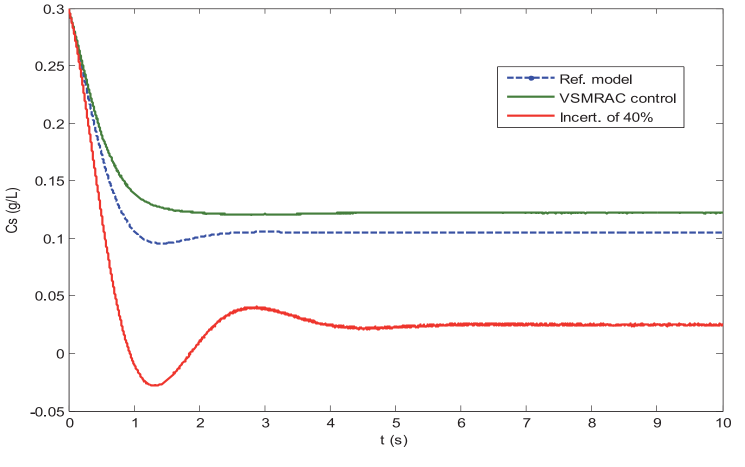

Figure 13.
Salinity tracking dynamics for uncertainty of 40%.

3.3.1 Findings

If we assume that the intermittence of sunshine does not, in any case, exceed 40% of its normal value, the dynamic model of sunshine cannot be more than 40% different from its reference model. Therefore, we can deduce that the dynamic of the system remains insensitive to the variations of the photovoltaic solar source. Thus, we have exceeded the problem of intermittent sunshine, thanks to the implemented VSMRAF control technique.

3.4 Performances of VSMRAF control for optimization of operating systems

From these experimental results, we can essentially deduce that even in the case of high uncertainties, the tracking error remains clearly low, the system remains stable with regard to disturbances due to variations in the sunshine.

Consequently, the control technique that we have developed is suitable for the optimization of operating systems coupled to photovoltaic solar sources. It keeps the stability of the system and eliminates the effect of sunshine variation on its dynamic behavior.

Simulations and experimental results prove our theoretical results and show a perfect following of the reference sunshine model independent of the variation of the photovoltaic solar source. The tracking error is less than 8% remains low even for high intermittence of sunshine not exceeding 40% of its maximum value.

The comparison of results mentioned by the curves for the two output parameters (water flow rate and salinity) of the PV-ROD system shows that the effect of the photovoltaic solar system variation was removed. In addition, experimental results justify the theoretical ones and show that this verified control technique for desalination systems can be generalized for all industrial systems coupled to photovoltaic solar sources having multivariable dynamic models.

4. Conclusion

In this chapter, a VSMRAF Control for systems coupled to photovoltaic solar systems has been proposed. This control technique decreases the sensitivity of the system to variations of solar energy caused by intermittent sunlight. In addition, this technique imposes on the system dynamics to follow the reference model imposed by the daily evolution of solar energy without recourse to the use of batteries.

Furthermore, the experimental and simulation results show that the following error of the system has been kept with a low value (less than 8%) even with a high variation of sunshine. Thus, we can conclude that using this control technique ensures the system's stability and neglects the effect of intermittence of sunshine.

The mathematical development was independent of the nature of the systems, which makes it possible to be applied to all industrial systems, especially those with a limited number of parameters. Obviously, the prospect of this work consists in applying this technique on other multivariable real systems with several parameters and with strongly random variations of the solar energy to better examine the performances of this technique of control.

Abbreviations

I_s	Current of saturation (A)
Q	Charge (C)
V_p	Photovoltaic voltage (V)
V_D	Voltage of diode (V)
R_{sh}	Resistance of cell surface (Ω)
R_s	Resistance of junction face (Ω)
K	Constant of Boltzmann: 1.38064852(79) × 10 J–23 J/K.T
T	Temperature (K)
I_p	Photovoltaic current (A)

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