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PREDICTIVE CONTROL OF A SOLAR POWER PLANT

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***Abstract*— This paper deals with the problem of modeling and control to the distributed collector field of a solar power plant at the solar platform of the Almeria. The main characteristic of this type of process is the primary source of energy (solar radiation) cannot be manipulated, In addition to the intensity of solar radiation depends on the variations of daily and seasonal cycle as cloud and moisture. The ability of generalized predictive control strategy, to drive the process output more closely to the reference trajectory in the presence of constraints on the input and output signals, and to anticipate and to eliminate the effects of both feed forward and feedback disturbances .It is very interesting to investigate its utility in a solar power plant in order to maintain temperature oil output more nearer to the reference temperature**

Keywords- renewable energy, distributed solar collector field, predictive control, subspace identification.

I. INTRODUCTION

Today solar energy represents the best source for the energy supply of the future. This work studies the fields solar collector distributes of the solar platform of the Almeria, situated in the south of Spain. One of the main features of this type of proceed solar energizing is that the source primary of energy (solar radiation) cannot be manipulated. In addition, the intensity of the solar radiation depends on the variations of the daily and seasonal cycle, as the clouds, the atmospheric humidity, and the turbidity of air. The main objective of the control is to maintain the temperature of oil in the exit more close to the order, in spite of the changes of the operative conditions, while manipulating the debit of oil. For it one proposes to use the strategy of a predictive control strategy based on state space models identified from actual data.

II. DESCRIPTION OF SYSTEM

The system studied here is the ACUREX distributed solar collector field. The PSA plant *(Plataforma Solar de Almeria)* based on a parabolic-trough technology, and located on the desert of Tabernas in the south of Spain. The field consists of 480 distributed solar collectors arranged in 20 rows, which form10 parallel loops. Every collector is composed of a parabolic surface that concentrates radiation solar direct toward the conduct placed in a parabolic focal line Fig.1. Each collector uses parabolic mirrors to concentrate the radiation in a receiver tube. Synthetic oil is pumped through the receiver tube and picks up the heat transferred through the tube walls. The cold inlet oil (at temperature *Tin*) is extracted from the bottom of a storage tank and is passed through the field using a pump at the field inlet. Then, the heated fluid is introduced into the storage tank to be used for electrical energy generation or for feeding a heat exchanger of a desalination plant.

Fig.1.The Buckles, The Conducts And The Vats Of The Solar Field.

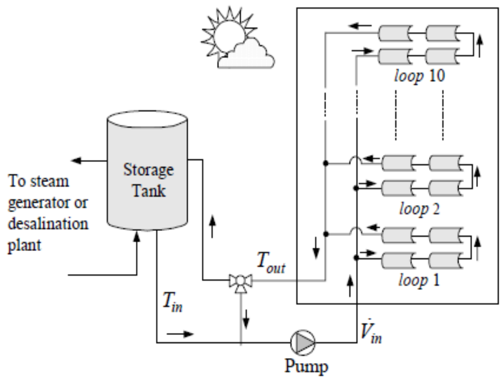

Fig .2. A Schematic Diagram Of The Acurex Solar Collector Field

solar field modeling

The dynamics of the solar field to distributed collectors are described by a set of non linear equations from the balances of mass and energy follow [11]:

$$\rho_m c_m A_m \frac{\partial T_m}{\partial t} = I\eta_0 D - h_L G(T_m - T_a) - Lh_T(T_m - T_f) \quad \text{Eq. (1)}$$

$$\rho_f c_f A_f \frac{\partial T_f}{\partial t} + V\rho_f c_f A_f = Lh_t(T_m - T_f) \quad \text{Eq. (2)}$$

Where ρ is density of oil (kg/m^3), c is specific heat of oil J/kg K), A is section of the tube (m^3), T is temperature (℃), I is solar radiation (W/m^2K), η_0 optic efficiency, D is width outside of the tube (m), h_L is coefficient of global thermal loss, G is outside diameter of the tube (m), T_a is temperature of the environment (℃), L is internal diameter of the tube (m), h_T is coefficient transmission metal-fluid (W / m^2K) and V is rate of the volumetric flux of oil.

III. SUBSPACE IDENTIFICATION METHOD

The subspace identification method permit to obtain a state space model of unknown linear systems from the given Input /output data. This method is based on the following steps:

. Use an orthogonal or oblique projection of the row spaces of certain block Hankel matrices of data into the row spaces of other block Hankel matrices;
. Apply a singular value decomposition (SVD) to determine the order, the observability matrix and /or the state sequence.
. Resolve a least squares problem to obtain a state space model.

Discrete time, linear, time-invariant, state space models can be described by the following set of difference equations [5],[7]:

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + w_k \\ y_k = Cx_k + Du_k + v_k \end{cases} \quad (3)$$

with

$$\boldsymbol{E}\left[\begin{pmatrix} w_p \\ v_p \end{pmatrix} \begin{pmatrix} w_p & v_p \end{pmatrix}\right] = \begin{pmatrix} Q & S \\ S^T & R \end{pmatrix} \delta_{pq} \geq 0 \quad \text{Eq. (4)}$$

where *x*, *u*, and *y* are respectively, the process states, inputs and outputs, , while A is the system (state transition) matrix, B is the input matrix, C is the output matrix and D is the direct input to output matrix. *w* is called the process noise and *v* is called the measurement noise. The matrices *Q, S* and *R* are the covariance matrices of the noise sequences w and v. **E** denotes the expected value operator and δ_{pq} the Kronecker delta.

The measured data are arranged in the Hankel form. matrices Y_f,Y_p,U_f and $U_p$where the subscripts "f" and "p" denote the future and past, respectively. The Hankel matrices can be arranged to form a linear regression equation:

$$Y_f = \begin{bmatrix} R_{U_p} & R_{Y_p} & R_{U_f} \end{bmatrix} \begin{bmatrix} U_p \\ Y_P \\ U_f \end{bmatrix} \quad \text{Eq.(5)}$$

This can be solved in a least squares sense. By excluding the linear combination of the U_f, the matrix of predicted outputs can be written as:

$$\hat{Y}_f = [R_{U_p} R_{Y_p}] \begin{bmatrix} U_p \\ Y_p \end{bmatrix} \quad \text{Eq.(6)}$$

It can be shown [7] that the input-state-output relations can be expressed as:

$$Y_f = \Gamma X_f + R_{U_f} U_f + E_f \quad \text{Eq. (7)}$$

Where Γ is the extended observability matrix, X_f is a matrix of state sequences stored as row vectors, and E_f is a noise term. By excluding U_f , the matrix of predicted outputs can be defined as:

$$\hat{Y} = \Gamma \hat{X}_f \quad \text{Eq. (8)}$$

Where $\hat{X}_f$ represent the predicted states, which are up to now known. By performing the singular value decomposition (SVD) of (6), deleting small singular values, and comparing to (8) gives

$$\hat{Y}_f = USV^T \approx U_1 S_1 V_1^T = \Gamma \hat{X}_f \quad \text{Eq.(9)}$$

$$\Gamma = U_1 S_1^{\frac{1}{2}} \qquad \hat{X}_f = \Gamma^+ \hat{Y}_f \quad \text{Eq. . (10)}$$

Where $+$ denotes the Moore-Penrose pseudoinverse. Once the matrix of states is given by(9), the state space model matrices can be found by solving a simple set of overdetermined equations in a least squares sense:

$$\begin{bmatrix} \hat{X}_{k+1} \\ Y_k \end{bmatrix} = \begin{bmatrix} A & B \\ c & D \end{bmatrix} \begin{bmatrix} \hat{X}_k \\ U_k \end{bmatrix} + v_k \quad \text{Eq. (11)}$$

With v_k as residual matrix. In addition, the Kalman gain k can then, if desired, be computed from A , c and the covariance matrix of v_k.

V. GENERALIZED PREDICTIVE CONTROL

Consider the following locally linearized controlled autoregressive and moving average (CARIMA) time discrete model [1], [3],[7],[13]:

$$A(q^{-1})y(k) = B(q^{-1})u(k-1) + e(k)/\Delta \qquad \text{Eq.(12)}$$

Where u(t), y(t) and e(t) are respectively the control input, the controlled variable, and uncorrelated random sequence at time k; q^{-1} is the backward shift operator, Δ is the differencing operator ($\Delta = 1 - q^{-1}$); and $A(q^{-1}), B(q^{-1})$ are polynomials obtained by instantaneous linearization method:

$$A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-1} + .. + a_{nA} q^{-nA}$$

$$B(q^{-1}) = b_0 + b_1 q^{-1} + b_2 q^{-2} + .. + a_{nB} q^{-nB} \qquad \text{Eq. (13)}$$

The objective of the generalized predictive control strategy is to minimize a cost function based on error between the predicted output of the process and the reference trajectory. The cost function is minimized in order to obtain the optimal control input that is applied to the non-linear plant. The cost function has the following quadratic form:

$$J = \sum_{i=N_1}^{N_2} [\hat{y}(k+j) - r(k+j)]^2 + \lambda \sum_{i=1}^{N_u} \Delta u^2(k+j-1) \qquad Eq.(14)$$

N_1 : the minimum prediction horizon;
N_2 : the maximum prediction horizon;
j : the order of the predictor;
r : the reference trajectory;
λ : weight factor;
Δ : the differentiation operator;

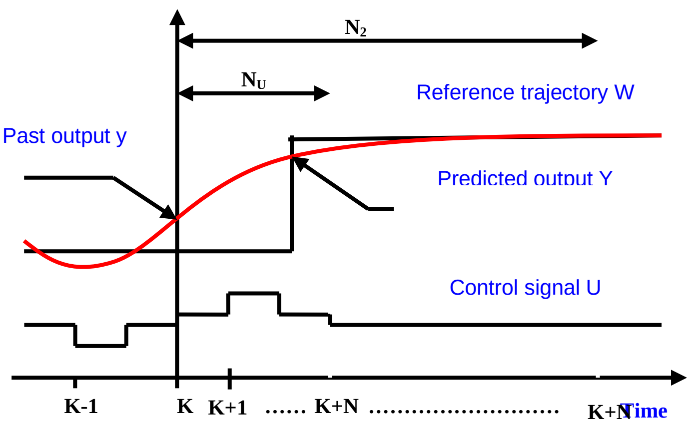

Fig.3. Generalized Predictive Control Strategy Principle

Thus, the goal is to drive the future outputs $y(k+j)$ close to $r(k+j)$ for N_1 =1 and $N_2 = N$ the prediction vector:

$\hat{Y} = [\hat{y}(k+1), \hat{y}(k+2), \ldots, \hat{y}(k+N)]^T$ is given by

$$\hat{Y} = G\Delta U + F \qquad \text{Eq.(15)}$$

Where $\Delta U = [\Delta U(k), \Delta U(k+1), \ldots, \Delta U(k+N-1)]^T$ and $F = [f(k+1), f(k+2), \ldots, f(k+N)]^T$ are the predictions of the output by assuming that future control increments are all zero. Then, the control law is given by:

$$\Delta U = (G^T G + \lambda I)^{-1} G^T (R - F) \qquad \text{Eq.(16)}$$

Where $R = [r(k+1), r(k+2), \ldots, r(k+N)]^T$ if after a certain horizon N_u , control horizon, the increments are assumed to be zero.

$$\Delta u(k+j-1) = 0 \,, \qquad 1 \leq N_u < j \leq N_2$$

The control law becomes:

$$\Delta U = ({G_1}^T G_1 + \lambda I)^{-1} {G_1}^T (R - F) \qquad \text{Eq.(17)}$$

$$G_1 = \begin{bmatrix} g_0 & 0 & \ldots. & 0 & \ldots\ldots & 0 \\ g_1 & g_0 & \ldots. & 0 & \ldots\ldots & 0 \\ \ldots. & \ldots. & \ldots. & g_{N-1}\ldots. & \ldots. & 0 \\ g_{N-1} & g_{N-2} & \ldots & \ldots. & \ldots. & g_{N-N_u} \end{bmatrix}$$

And the matrix $({G_1}^T G_1 + \lambda I)$ is $N_u * N_u$
The coefficients of the matrix G_1 can be obtained from polynomials G_j given by :

and E_j results from the recursive solution of the Diophantine equation:

$$1 = E_j(q^{-1})A(q)^{-1}\Delta + q^{-j}F_j(q^{-1}) \qquad \text{Eq. (19)}$$

deg (E_j) =j-1, deg (F_j)=n

As the cost function used in GPC is quadratic, then quadratic programming (QP) techniques are well suited for solving the problem of constraints on the control signal, the output signal or on the increments of the control signal.

$$U_{\min} \le U \le U_{\max} \quad \text{Eq.(20)}$$

$$Y_{\min} \le Y \le Y_{\max} \quad \text{Eq.(21)}$$

$$\Delta U_{\min} \le \Delta U \le \Delta U_{\max} \quad \text{Eq. (22)}$$

VI. RESULTS AND DISCUSSIONS

First time, the subspace identification method is used to find the state space model of the Acurex Solar Collectors Field of the *Plataforma Solar de Almería* (PSA) directly from the data of input corresponding to [q_s ,T_{in},I_{rr}] and of output corresponding to [T_{out}]. The data and the model output are so close to each other (Fig.4,5,6,7). In the second time, predictive control strategy is applied to this type of system. The results show that the predictive controller is able to drive the output close to the reference trajectory by selecting the best choice of the parameters values like prediction horizon, control horizon and the weight factor in spite of the variations of the input temperature and the solar irradiation (Fig.8, 9).

The matrix of the state space model are:

$$A = \begin{bmatrix} 0.9282 & 0.0842 & 0.1360 & 0.1402 \\ -0.1861 & 0.9152 & 0.1335 & -0.0043 \\ 0.0262 & -0.0774 & 0.6776 & -0.7024 \\ -0.1052 & 0.1386 & 0.4674 & 0.4537 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.0703 & 0.0060 & 0.0171 \\ 0.0401 & 0.0072 & 0.0094 \\ -0.2853 & -0.0159 & -0.0618 \\ -0.0576 & 0.0127 & -0.0080 \end{bmatrix}$$

$$C = [131{,}7858 \quad -40{,}9384 \quad 29{,}8142 \quad -3{,}6725]$$

$$D = [0 \quad 0 \quad 0]$$

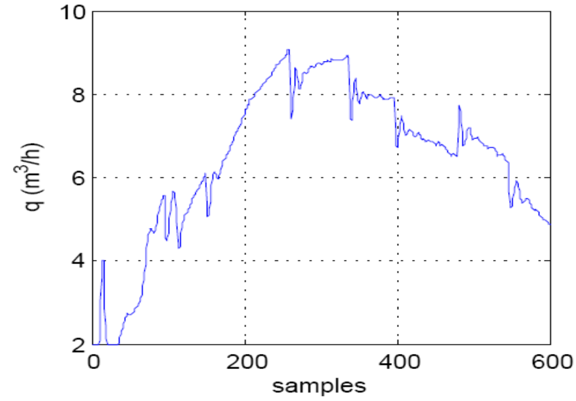

Fig.4.Data Sequence of Fluid Flow

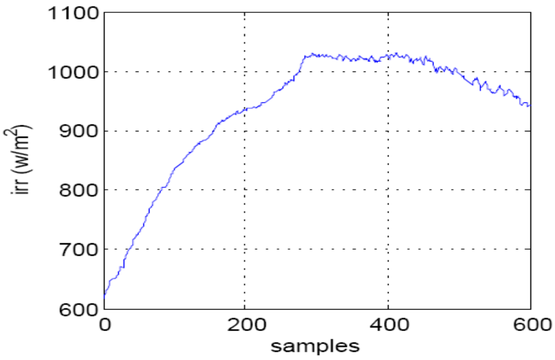

Fig.5.Data Sequence of Solar Radiation

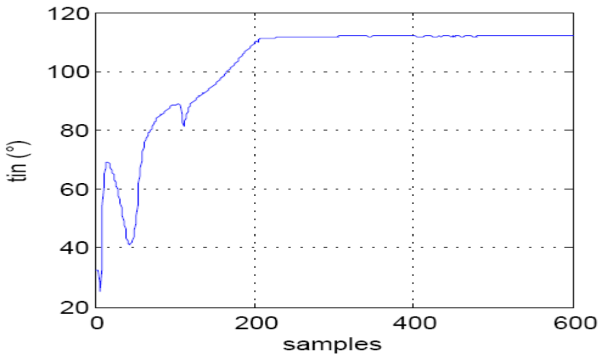

Fig.6.Data Sequence of Inlet Temperature

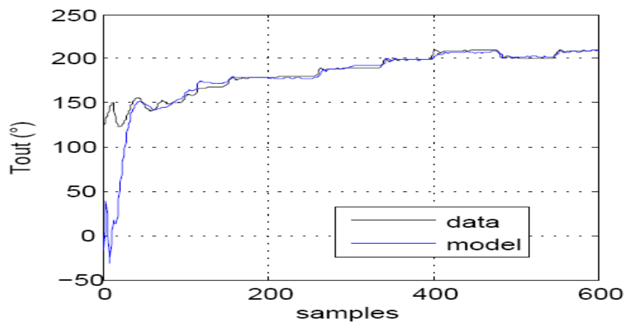

Fig.7. Data Sequences and Model output (Outlet Temperature)

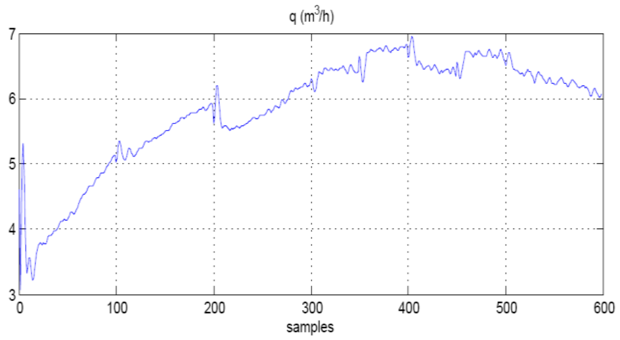

Fig.8. Control Signals

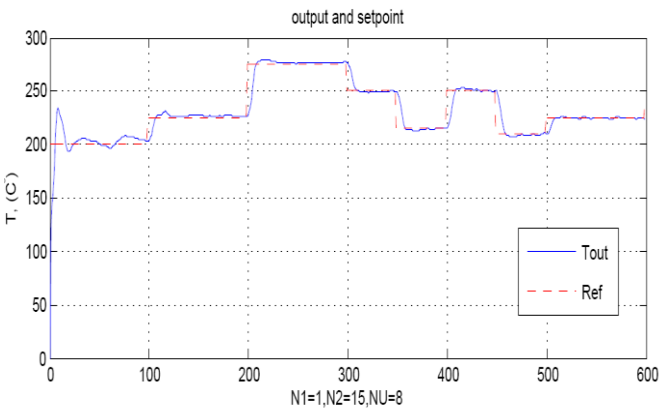

Fig.9. Setpoint, Output Temperature.

VII. CONCLUSION

In this work, we have used the identification subspace method for modeling Acurex Solar Collectors Field of the *Plataforma Solar de Almería* and the predictive control strategy to insure the following of the reference trajectory. The obtained results are satisfactory and we plan to improve them by the use of other techniques of modeling and control.

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