Multivariable input-output linearising control of an autonomous power system

The input-output and state feedback control of nonlinear systems has been the object of a number of applications in robotics, chemical and biochemical processes, and electric motors for instance. Here we consider the application of input-output linearisation to a laboratory-scale autonomous power system. The control problem considered here is multivariable and consists of controlling the power system frequency and the load voltage by acting on the excitation voltage and on the dc motor voltage. The nonlinear dynamical model has been derived by using the Lagrange laws and has been validated with experimental data. The nonlinear dynamical model has been used for the derivation of the input-output decoupling linearising controller. The stability of the zero dynamics is analysed, and the performance of the linearising controller is illustrated by simulation results.

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Introduction

The design of linearising controllers for nonlinear dynamical systems has been a very active research area for more than a decade [7], [12] and has already given rise to a number of applications in various fields including robotics [4], chemical and biochemical processes [5], [6], [1] and electric motors [2]. Several papers have been dedicated to the design of nonlinear control laws for electric generators . In [9], the full state feedback linearising regulator is designed for a synchronous generator described by a fifth-order dynamical model with two control inputs, the rotor angular acceleration and the field excitation voltage. [3] concentrates on the design of a state feedback linearising controller on the basis of a fourth-order nonlinear model with one control input, the rotor field voltage. In [8], the same model as in [3] is used to design a SISO (single input single output) input-output linearising controller where the controlled output is the generator terminal voltage and the control input, the rotor field voltage.

In this paper, we shall concentrate on the design of a MIMO (multi input multi output) input-output linearising control scheme for an autonomous power system. As for any nonlinear system, the objective is to introduce in the controller design the well-known nonlinearities of the system dynamics in such a way that the closed-loop dynamics are linear. Unlike in the abovementioned papers [9], [3], [8], where the feedback linearisation is based on Park's equations, here the control design is based on the autonomous power system state equations, and therefore does not require the double transformation of the variables to be manipulated. Moreover in the abovementioned papers [9], [3], [8], the generators are assumed to be connected to an infinite bus: although this assumption may be acceptable (although not perfect) for a large power systems, this is clearly not acceptable for mini autonomous systems (as the one being studied here). The dynamical model of the autonomous power system has been deduced by considering the Lagrange method, and it has been validated on a laboratory-scale power system [11]. Here we have considered an input-output linearising control law, whose design is mathematically less involved than a full state feedback linearising control scheme, but which is based on the assumption of stable zero dynamics. Moreover the control problem is a multivariable one, i.e. the control of the power system frequency and the load voltage by acting on the excitation voltage and on the dc motor mvoltage.

The paper is organised as follows. Section 2 briefly recalls the basics of the input-output decoupling linearisation. Section 3 introduces the dynamical model of the autonomous power system being studied. Section 4 deals with the design of the input-output linearising controller for the autonomous power system and wiith the analysis of the zero dynamics. And finally section 5 presents simulation results which illustrate the performance of the linearising controller.

Multivariable input-output decoupling linearising control

The control problem

Let us briefly recall the basics of the input-output decoupling linearising control design. Let us first consider a system with n states, m inputs and m outputs whose dynamics are described by the following nonlinear state space model:

$$\frac{dx}{dt} = f(x) + \sum_{i=1}^{m} g_i(x)\, u_i \tag{1}$$

$$y_j = h_j(x) \qquad j = 1 \text{ to } m \tag{2}$$

where x is the state vector ($x \in R^n$), and u and y are the input and output vector (with the same dimension (= m)):

$$u = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_m \end{bmatrix}, \quad y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} \tag{3}$$

Assume that the control objective consists of controlling the m outputs by acting on the m inputs. If v is the external input, the input-output linearisation of the system (1) (2) consists of designing a feedback law:

$$u = \alpha(x) + \beta(x)v \tag{4}$$

and a change of coordinates:

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} = T(x) \tag{5}$$

such that with the coordinates z(x), the closed-loop dynamics of the output variable vector y is linear and decoupled.

The controller design

Let us consider the following vector of characteristic numbers:

$$\sigma = \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_m \end{bmatrix} \tag{6}$$

defined as follows:

$$(L_{g1} L_f^{(k)} h_j \ldots L_{gm} L_f^{(k)} h_j) = (0 \ldots 0) \quad \text{for } k = 0 \text{ to } \sigma_j - 1 \tag{7}$$

$$(L_{g1} L_f^{(\sigma j)} h_j \ldots L_{gm} L_f^{(\sigma j)} h_j) \neq (0 \ldots 0) \tag{8}$$

where $L_{gi} L_f^{(k)} h_j$ is defined as follows:

$$L_f^{(0)} h_j = h_j \tag{9}$$

$$L_f^{(1)} h_j = \frac{\partial h_j}{\partial x} f \tag{10}$$

$$L_{gi} L_f^{(k)} h_j = \frac{\partial\, [L_f^{(1)} (L_f^{(k-1)} h_j)]}{\partial x} g_i \tag{11}$$

i.e. each characteristic number σ_j is the minimal integer for which $L_{gi} L_f^{(\sigma j)} h_j$ is not identically zero.

Let us also define the following decoupling matrix:

$$D(x) = \begin{bmatrix} L_{g1} L_f^{(\sigma 1)} h_1(x) & \ldots & L_{gm} L_f^{(\sigma 1)} h_1(x) \\ L_{g1} L_f^{(\sigma 2)} h_2(x) & \ldots & L_{gm} L_f^{(\sigma 2)} h_2(x) \\ \ldots & \ldots & \ldots \\ L_{g1} L_f^{(\sigma m)} h_m(x) & \ldots & L_{gm} L_f^{(\sigma m)} h_m(x) \end{bmatrix} \tag{12}$$

It is shown in [12] that:

$$\begin{bmatrix} h_1^{(\sigma 1+1)}(x) \\ \vdots \\ h_m^{(\sigma m+1)}(x) \end{bmatrix} = \begin{bmatrix} L_f^{(\sigma 1+1)} h_1(x) \\ \vdots \\ L_f^{(\sigma m+1)} h_m(x) \end{bmatrix} + D(x)u \tag{13}$$

$$= L(x) + D(x)\,u \tag{14}$$

It can be shown (e.g. [7], [12]) that if D(x) is non singular, then there exists a solution to the input-output decoupling linearising control problem. In that case, the linearising decoupling feedback law is given by introducing in equation (4) the following expressions for $\alpha(x)$ and $\beta(x)$:

$$\alpha(x) = -[D(x)]^{-1} L(x) \tag{15}$$

$$\beta(x) = [D(x)]^{-1} \tag{16}$$

And the immersion law is given by the following relationships:

$$z_1^1 = T_1 = L_f^{(0)} h_1, \ldots, z_{\sigma 1+1}^1 = T_{\sigma 1+1} = L_f^{(\sigma 1)} h_1 \tag{17}$$

$$z_1^j = T_{1+\sum_{k=1}^{j-1}(\sigma_k+1)} = L_f^{(0)} h_j, \ldots, \tag{18}$$

$$z_{\sigma j+1}^j = T_{\sum_{k=1}^{j}(\sigma_k+1)} = L_f^{(\sigma j)} h_j, \text{forallj} = 1\text{tom} \tag{19}$$

$$z_{r+1} = \Phi_1, \ldots, z_n = \Phi_{n-r} \text{ where } r = \sum_{j=1}^{m} (\sigma_j + 1) \tag{20}$$

$$L_f^{\sigma 1+1} h_1 = v_1, \ldots, L_f^{\sigma m+1} h_m = v_m \tag{21}$$

In the coordinate system (z(x), the solution is the combination of two submanifolds of dimension r and n-r, respectively. The equivalent normal form of the original system is written als follows:

$$\dot{z}^j = \begin{bmatrix} 0 & 1 & 0 & . & . & . & 0 \\ 0 & 0 & 1 & 0 & . & . & . \\ . & . & 0 & 1 & . & . & . \\ . & . & . & 0 & . & . & . \\ . & . & . & . & . & 1 & . \\ . & . & . & . & . & 0 & 1 \\ 0 & . & . & . & . & . & 0 \end{bmatrix} z^j + \begin{bmatrix} 0 \\ . \\ . \\ . \\ . \\ . \\ 1 \end{bmatrix} v_j \tag{22}$$

$$\begin{bmatrix} \dot{z}_{r+1} \\ \vdots \\ \dot{z}_n \end{bmatrix} = \Phi^T(x,u) \tag{23}$$

Dynamical model of the autonomous power system

The autonomous power system under study is schematised in *Figure 1.* The dynamical model has been developed by considering the Lagrange laws. This led to a full order state space model and a reduced order model (which has been obtained from the full order one basically by assuming that the mechanical time constants are larger than the electrical ones and that the power system is electrically and electromagnetically balanced). Both models have been validated on the basis of experimental data (for further details, see [11], [10]. The reduced order model which has been used for control design is written as follows:

$$\frac{d}{dt}\begin{bmatrix} I_m \\ I_{fg} \\ \Omega \\ \delta \end{bmatrix} = \begin{bmatrix} -\frac{R_m}{L_m} I_m - \frac{K_m}{pL_m}\Omega \\ -\frac{R_{fg}}{L_{fg}} I_{fg} \\ \frac{K_m p}{J} I_m - \frac{F}{J}\Omega - \frac{3pK_g^2}{2JL_g} I_{fg}^2 \sin(2\delta) \\ \Omega - \frac{R_0}{L_g} \mathrm{tg}(\delta) \end{bmatrix} + \begin{bmatrix} \frac{A_m}{L_m} & 0 \\ 0 & \frac{A_g}{L_{fg}} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_m \\ v_{fg} \end{bmatrix} \qquad (24)$$

where I_m is the armature current of the motor, I_{fg} the synchronous machine excitation current, Ω the power system frequency, δ the electromagnetic power angle, v_m the HP amplifier voltage, v_{fg} McFadden amplifier voltage, R_m the armature resistance of the motor, L_m the armature inductance of the motor, K_m the torque constant, p the number of poles, R_{fg} the excitation circuit resistance, L_{fg} the inductance of the synchronous machine exciter, J the moment of inertia of all the rotating masses, F the damping coefficient, K_g the synchronous machine electromotive force coefficient, L_g the synchronous motor cyclic inductance, R_0 the load resistance per phase, A_m the HP amplifier gain and A_g the McFadden amplifier gain.

The following values have been identified for the system parameters [11], [10]:

$$R_m = 0.47\ (\Omega),\ L_m = 0.03\ (H),\ K_m = 0.582\ (V.s/rad), \qquad (25)$$

$$J = 0.1359\ (Kg.m^2),\ F = 0.0029\ (N.m.s/rad) \qquad (26)$$

$$p = 2,\ R_{fg} = 39\ (\Omega),\ L_{fg} = 8\ (H),\ L_g = 0.0175\ (H) \qquad (27)$$

$$R_g = 0.6\ (\Omega),\ K_g = 0.26\ (V.s/A.rad) \qquad (28)$$

$$A_g = 14.6,\ A_m = 22 \qquad (29)$$

Design and analysis of the input-output linearising controller of the autonomous power system

Definition of the control problem

The control problem is basically a multivariable control problem. Indeed in an autonomous power system, the symplifying assumption that the excitation loop allows to control the voltage and to stabilise the speed is unfortunately not always valid.

The outputs of the autonomous power system are the power system frequency Ω and the load voltage V_0 (see Figure 1). The power system frequency is a state variable of the nonlinear dynamical model of the system (24), and the load voltage is related to the system equations via the following relationship:

$$V_0 = K_g I_{fg} \Omega \cos(\delta) \qquad (30)$$

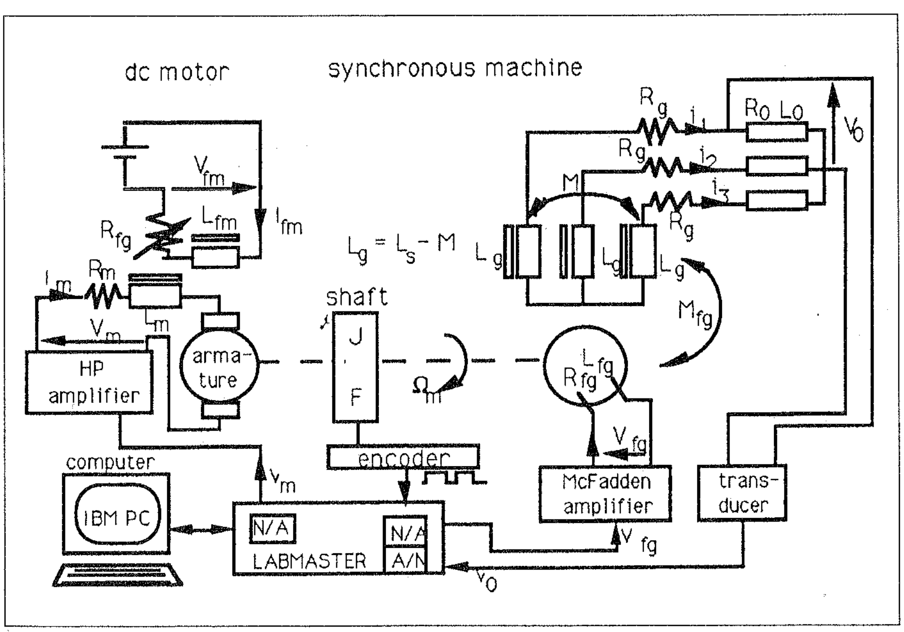

Fig. 1: Schematic view of the autonomous power system.

This can be formalised as follows:

$$y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \Omega \\ K_g I_{fg} \Omega \cos(\delta) \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} \qquad (31)$$

Assume that we wish to control both outputs by acting on the dc motor voltage V_m and on the excitation voltage V_{fg}, or more precisely the value of the voltages applied to both HP and McFadden amplifiers, v_m and v_{fg}, i.e.:

$$u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} v_m \\ v_{fg} \end{bmatrix} \qquad (32)$$

Let us compute the characteristic numbers σ_j from equations (7) and (8). If we consider the values of the state variables such that:

$$I_{fg} \neq 0, \Omega \neq 0 \text{ and } 0 < \delta < \frac{\Pi}{2} \tag{33}$$

we can conclude, after somewhat long but straightforward calculations, that:

$$\sigma_1 = 1, \sigma_2 = 0 \tag{34}$$

Note that there is no problem in excluding for the linearising control design the singular points of (33) since these do not correspond to standard operation values of the autonomous power system.

Decoupling matrix D(x)

The decoupling matrix is readily deduced from (12) and (24):

$$D(x) = \begin{bmatrix} \frac{A_m K_m p}{JL_m} & -\frac{3pK_g^2 A_g}{JL_g L_{fg}} I_{fg} \sin(2\delta) \\ 0 & \frac{K_g A_g}{L_{fg}} I_{fg} \cos(\delta) \end{bmatrix} \tag{35}$$

$$= \begin{bmatrix} D_1 & D_2 \\ 0 & D_4 \end{bmatrix} \tag{36}$$

The determinant of D(x) is equal to $\frac{A_m K_m p K_g A_g}{JL_m L_{fg}} I_{fg} \cos(\delta)$. Therefore D(x) is invertible if $I_{fg} \neq 0$ and $\delta \neq \frac{\Pi}{2}$. In that case, The inverse of D(x) is then equal to:

$$D^{-1}(x) = \begin{bmatrix} \frac{JL_m}{A_m K_m p} & -\frac{6K_g L_m}{A_m K_m L_g} I_{fg} \sin(2\delta) \\ 0 & \frac{L_{fg}}{K_g A_g I_{fg} \cos(\delta)} \end{bmatrix} \tag{37}$$

$$= \begin{bmatrix} D_5 & D_6 \\ 0 & D_8 \end{bmatrix} \tag{38}$$

Linearising control law

The functions α(x) and β(x) introduced in equation (4) and defined in equations (15) and (16) are here equal to:

$$\alpha(x) = \begin{bmatrix} -D_5 L_1 - D_6 L_2 \\ -D_8 L_2 \end{bmatrix} \tag{39}$$

$$\beta(x) = \begin{bmatrix} D_5 & D_6 \\ 0 & D_8 \end{bmatrix} \tag{40}$$

with:

$$\begin{aligned} L_1 = & -\frac{K_m p}{J}\left(\frac{R_m}{L_m} + \frac{F}{J}\right) I_m + \left(\frac{F^2}{J^2} - \frac{K_m^2}{L_m J}\right)\Omega \\ & + \frac{3pK_g^2 R_{fg}}{JL_g L_{fg}} + \frac{3pK_g^2 F}{2J^2 L_g}) I_{fg}^2 \sin(2\delta) \\ & - \frac{3pK_g^2}{JL_g} I_{fg}^2 [\Omega - \frac{R_0}{L_g} t_g(\delta)] \cos(2\delta) \end{aligned} \tag{41}$$

$$\begin{aligned} L_2 = & -K_g \frac{R_{fg}}{L-fg} I_{fg} \Omega \cos(\delta) \\ & + K_g I_{fg} \cos(\delta) [\frac{K_m p}{J} I_m - \frac{F}{J}\Omega] \\ & - \frac{3pK_g^2}{2JL_g} I_{fg}^2 \sin(2\delta) \\ & - K_g L_{fg} \Omega [\Omega - \frac{R_0}{L_g} tg(\delta)] \sin(\delta) \end{aligned} \tag{42}$$

Normal form and zero dynamics

The dimension of the considered linear decoupled submanifold is equal to $2 + \sigma_1 + \sigma_2 = 3$. In this submanifold, the immersion law $z = T(x)$ of the original nonlinear system is readily deduced from equation (13) and takes the following form:

$$z_1^1 = L_f^{\sigma 1} h_1(x) = h_1(x) = \Omega \tag{43}$$

$$z_1^2 = L_f^{\sigma 2} h(x) = h_2(x) = K_g I_{fg} \Omega \cos(\delta) \tag{44}$$

$$\dot{z}_1^1 = z_2^1 = \frac{K_m p}{J} I_m - \frac{F}{J}\Omega - \frac{3pK_g^2}{2J L_g} I_{fg}^2 \sin(2\delta) \tag{45}$$

$$\dot{z}_2^1 = v_1 \tag{46}$$

$$\dot{z}_1^2 = v_2 \tag{47}$$

The dimension of the submanifold which becomes unobservable by feedback is equal to $4 - (2 + \sigma_1 + \sigma_2) = 1$. We know (e.g. [7]) that if the distribution $G = \text{Span}(g_1, ..., g_m)$ is involutive, we can find $\Phi = [z_{r+1}, ..., z_n]^T$ such that $L_{gi}\Phi(x) = 0$ (i = 1 to m) and such that the Jacobian matrix of the global transformation $(T(x)\ \Phi(x))^T$ is non singular. Here the involutivity condition is fulfilled since the Lie bracket $[g_1\ g_2] = 0$ and belongs to the subspace generated by Span $(g_1\ g_2)$. The partial differential equation system $[L_{g1}\Phi(x)\ L_{g2}\Phi(x)] = 0$ has to be solved in order to deduce $\Phi(x)$, i.e.:

$$\begin{bmatrix} \frac{\partial\Phi}{\partial I_m} & \frac{\partial\Phi}{\partial I_{fg}} & \frac{\partial\Phi}{\partial\Omega} & \frac{\partial\Phi}{\partial\delta} \\ \frac{\partial\Phi}{\partial I_m} & \frac{\partial\Phi}{\partial I_{fg}} & \frac{\partial\Phi}{\partial\Omega} & \frac{\partial\Phi}{\partial\delta} \end{bmatrix} \begin{bmatrix} \frac{A_m}{L_m} & 0 \\ 0 & \frac{A_g}{L_{fg}} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{48}$$

It is straightforward from the above equations that a function $\Phi(x)$ independent of I_m and I_{fg} will be the solution of the equations (48). A possible choice is then:

$$\Phi(x) = \delta - \bar{\delta} = z_4(x) \tag{49}$$

where $\bar{\delta}$ is the steady-state value of the electromagnetic power angle δ. The dynamics of Φ are given by the following equation:

$$\dot{z}_4 = z_1^1 - \frac{R_0}{L_g} \operatorname{tg}(z_4 + \bar{\delta}) \tag{50}$$

Finally the normal form of the decoupled linearised system is written as follows:

$$\begin{bmatrix} \dot{z}_1^1 \\ \dot{z}_2^1 \\ \dot{z}_1^2 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} z_1^1 \\ z_2^1 \\ z_1^2 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \tag{51}$$

$$\dot{z}_4 = z_1^1 - \frac{R_0}{L_g} \operatorname{tg}(z_4 + \bar{\delta}) \tag{52}$$

$$y_1 = z_1^1 \tag{53}$$

$$y_2 = z_1^2 \tag{54}$$

Let us now study the stability of the zero dynamics. These are defined by the dynamics of z_4 at the equilibrium values of z_1^1, z_1^2 and z_2^1, i.e. if we denote by $\bar{\Omega}$ the steady-state value of z_1^1:

$$\dot{z}_4 = \bar{\Omega} - \frac{R_0}{L_g} \operatorname{tg}(z_4 + \bar{\delta}) \tag{55}$$

By considering trigonometric rules, the above equation (55) can be rewritten as follows:

$$\dot{z}_4 = -\frac{R_0}{L_g} (\operatorname{tg}^2 \delta + 1) \frac{\operatorname{tg}(z_4)}{1 - \operatorname{tg}(z_4)\operatorname{tg}(\delta)} \tag{56}$$

The analysis of the zero dynamics is intrinsically local. Let us consider the following candidate Lyapunov function $V = \frac{1}{2} z_4^2$. Its time derivative is equal to:

$$\dot{V} = -\frac{R_0}{L_g} (\operatorname{tg}^2 \delta + 1) \frac{z_4 \operatorname{tg}(z_4)}{1 - \operatorname{tg}(z_4)\operatorname{tg}(\delta)} \tag{57}$$

If we restrict the values of z_4 to the domain $]-\frac{\Pi}{2}, \frac{\Pi}{2}[$ and by recalling that we have considered values of δ ranging between 0 and $\frac{\Pi}{2}$ ($0 < \delta < \frac{\Pi}{2}$), it is straightforward to check that the zero dynamics (55) will be (locally) asymptotically stable for $-\frac{\Pi}{2} < z_4 < \frac{\Pi}{2}$ and $0 < \delta < \frac{\Pi}{2}$. Therefore, we can say that the linearising decoupling control law is applicable to the autonomous power system within the bounds defined above for z_4 (i.e. in other words as long as δ does not "deviate" too much

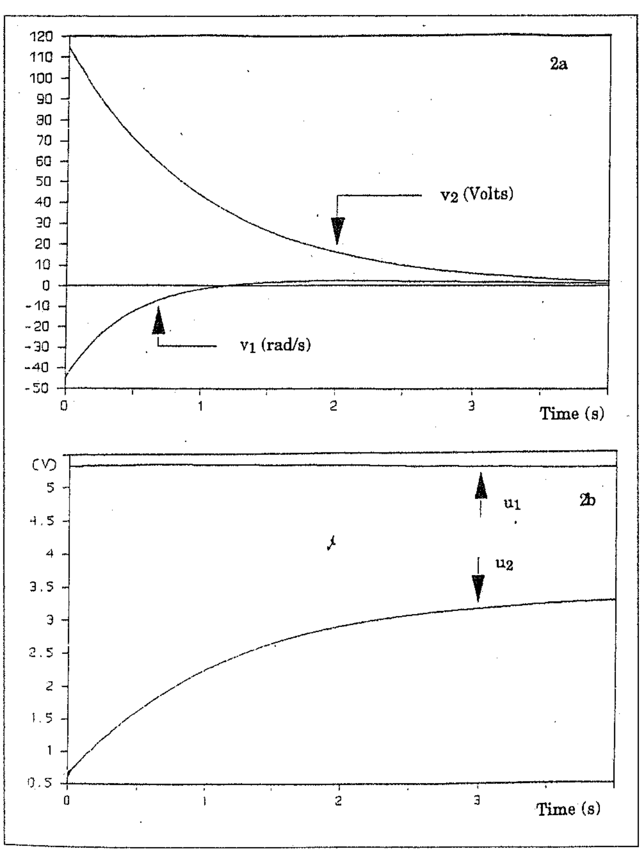

Fig. 2 a+b: Decoupling linearising control of an autonomous power system.

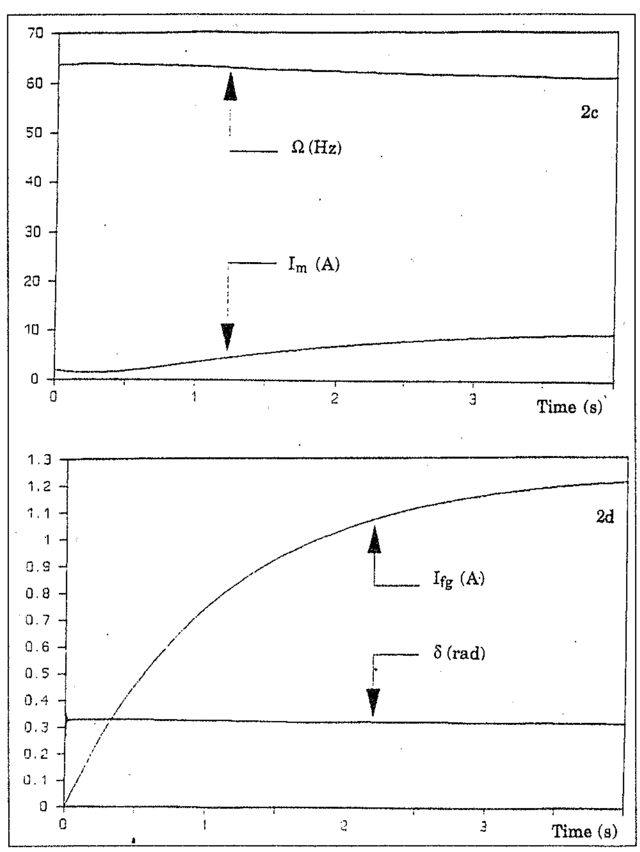

Fig. 2 c+d: Decoupling linearising control of an autonomous power system.

from its steady state value (note that this deviation may be quite large, particularly if $\bar{\delta}$ is small)).

Computation of the external inputs v

The external inputs v_1 and v_2 are computed by using the following equation:

$$v = w + C \begin{bmatrix} z_1^1 \\ z_1^2 \\ z_2^1 \end{bmatrix} \qquad (58)$$

where w is the external reference signal and a control gain matrix whose values are chose by considering a pole placement approach.

Simulation Results

The decoupling linearising control law (4) (39) (40) has been tested in simulation. *Figures 2 to 5* show several typical simulation results, where the closed loop poles have been assigned to the following values:

$$\text{Frequency loop } (\Omega) : = p_1 = -2.5,\ p_2 = -0.02 \qquad (59)$$

$$\text{Voltage loop } (V_0) : = p_3 = -0.985 \qquad (60)$$

This gives the following gain matrix C:

$$C = \begin{bmatrix} 1 & -2.55 & 0 \\ 0 & 0 & -0.985 \end{bmatrix} \qquad (61)$$

The following initial conditions have been considered:

$$I_m(0) = 2\text{ A},\ I_{fg} = 0\text{ A},\ \Omega(0) = 400\text{ rad/s},\ \delta(0) = 0\text{ rad} \qquad (62)$$

Figure 2a shows the external inputs $v_1(t)$ and $v_2(t)$, and *Figure 2b* the inputs $v_m(t)$ and $v_{fg}(t)$. Note that the variations of the inputs remain close to 6 Volts, which corresponds to the saturation signal of the power amplifiers of the N/A circuit. The closed loop behaviour of the state variables I_m, I_{fg}, Ω and δ are shown in *Figures 2c* and *2d. Figure 2* shows that it is possible to start from an arbitrary initial condition in the admissible state space, and to converge to the desired set point. Moreover since the system is decoupled, $v_1(t)$ only acts on Ω, and the value of the input u_1 results from the combination of the two inputs $v_1(t)$ and $v_2(t)$ in expression (4): this explains why in this specific example, u_1 is not varying very much, at least in comparison with u_2.

Figure 3 shows the output V_0 and Ω when a step of 50 rad/s (i.e. 7.96 Hz) is applied to the reference signal of the frequency, w_1. In *Figure 4*, we can see the time evolution of the outputs when a step of 50 Volts is applied to the reference signal of the voltage, w_2. Note in both cases the effectiveness of the decoupling on the closed loop behaviour of both outputs, and that the controlled output y_1 (y_2) closely follows the external output v_1 (v_2). We have deliberately chosen the same time scale for both *Figures 3* and *4* in order to emphasise that the speed loop is slow compared to the voltage loop.

Finally *Figure 5* shows the closed loop performance of the system when a load variation (a step of - 15 Ω) is applied to the system. Note the fast response of the system, which remains stable.

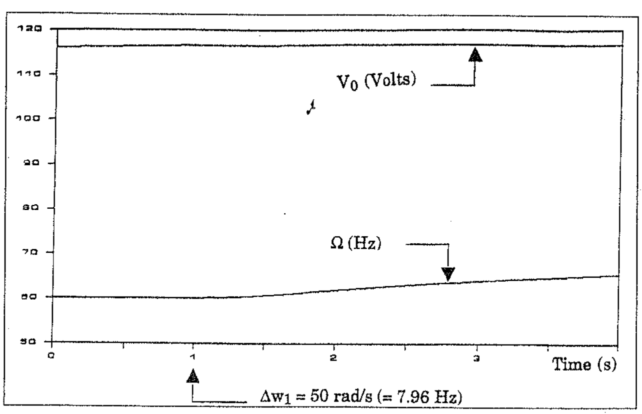

Fig. 3: Closed loop response to a step of the frequency reference signal w_1.

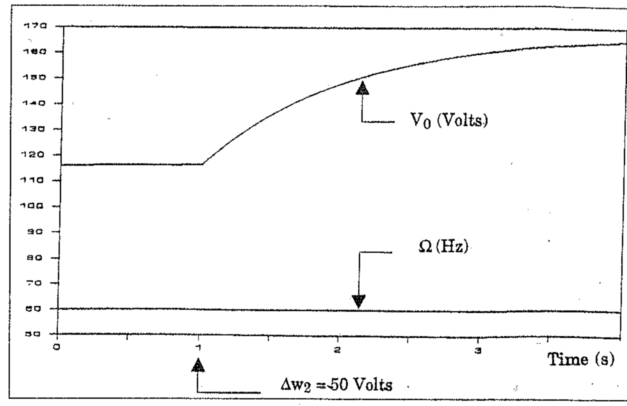

Fig. 4: Closed loop response to a step of the voltage reference signal w_2.

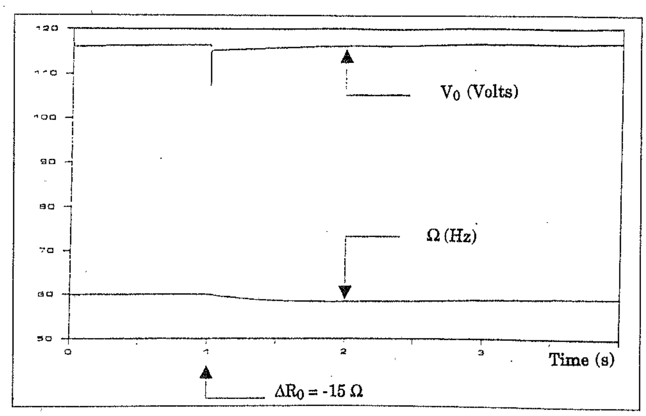

Fig. 5: Closed loop response to a disturbance step of the load R_0.

Conclusions

In this paper we have considered the application of multivariable input-output linearisation to a laboratory-scale autonomous power system. The control problem considered here is multivariable and consists of controlling the power system frequency and the load voltage by acting on the excitation voltage and on the dc motor voltage. The nonlinear dynamical model has been derived by using the Lagrange laws and has been the object of an experimental validation based on real-life data from a laboratory-scale power system. The nonlinear dynamical model has been used for the derivation of the input-output decoupling linearising controller. The stability of the zero dynamics has been analysed, and the performance of the linearising controller has been illustrated by simulation results.

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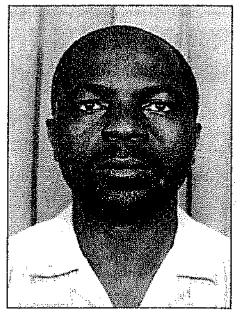

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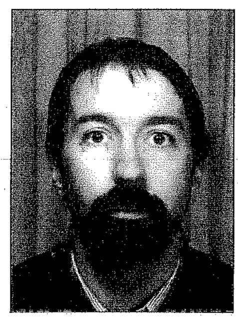

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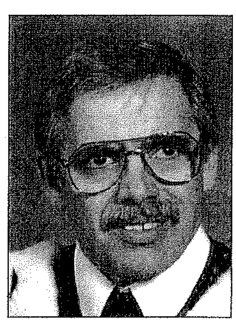

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