Forecasting Employability in Earth Sciences: The CIPEGE Tool

C. Garrouste* and E. Courtial†‡

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Abstract

Energy prices and environmental policies influence more than ever employment trends across the world. The purpose of this paper is to develop a strategy to enhance the employability of French graduates in a field that is both a key driver and a significant target of these new trends, namely Earth Sciences. The aim is to provide French universities with a predictive tool to adjust efficiently their skills' supply capacity with the demand forecasts at the European level. This task is treated as a tracking problem from the viewpoint of the control theory. The reference trajectory is obtained via a labour market forecasting model. For the first time, an econometric model and a predictive control strategy are combined. Simulations illustrate the feasibility and potentials of the proposed approach.

1 Introduction

In the past two decades, energy consumption, sustainable development and environmental protection have become priorities of energy policies in most countries (Kyoto Protocol, Grenelle environment in France, Carbon plan in the United Kingdom, 20-20-20 targets in the European Union). The transition to renewable energies is leading to many changes in the economy as a whole, in labour markets structure and dynamics, in societal behavior, and in research and education. Among the study and research disciplines

*Corresponding author: Laboratory of Economics of Orléans, University of Orléans, CNRS, UMR7322, Orléans, France (e-mail: christelle.garrouste@univ-orleans.fr).

†Laboratory PRISME, University of Orléans, EA4229, Orléans, France (e-mail: estelle.courtial@univ-orleans.fr).

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the most affected by these changes is Earth Sciences (ES). ES includes the study of atmosphere, hydrosphere, oceans and biosphere as well as solid Earth. Among the many challenges, the management of mineral resources is a real challenge for the society and the environment (green mining) because of its direct impact on consumption and labour. For instance, rare-earth minerals (REM) are increasingly used for the production of high-tech items such as smart phones, laptops but also in magnets for wind turbines, hybrid-car batteries, etc. After a misleading forecasting of its own consumption needs, the U.S. lost its leading producer position in favour of China and is now constrained to import at a very high price the goods it used to produce domestically. As a consequence of the closure of the mining extractions in the 1990s, the U.S. also decreased its investments in the training of solid ES scientists. While it now faces the need to re-open its REM mining sites to satisfy an increasing demand for high-tech goods, it suffers from a deficit in qualified Earth System scientists. A similar deficit affects Australia and Canada.

With its technical and scientific competences, its historical assets and its first-class actors in the field of ES, France aims at becoming a worldwide leader in the ES training. In 2011, the French Ministry of Higher Education nominated the project VOLTAIRE as a LABEX (Laboratory of excellence). Among the tasks of this project is the construct of an anticipation tool to ensure the employability of Earth System scientists trained in French universities. The CIPEGE center (Centre International de Prospective pour l'Emploi en Géosciences et Environnement - International Center for the Strategic Foresight of Employment in Earth and Environmental Sciences) was created to handle this task. In the sequel, the anticipation tool will be called the CIPEGE tool. This paper presents the innovative forecasting strategy adopted to develop the CIPEGE tool, which combines economics (an econometric model) and control process strategies (a model predictive control).

The employability of French ES graduates is measured and forecasted using a labour market micro-econometrics model, controlling for European macroeconomic trends. The task of this study is then to track the reference trajectory of the forecasted employability for the French graduates in ES. This objective can be viewed as a tracking problem from a control theory perspective. Among the existing advanced control laws, Model Predictive Control (MPC) is a control strategy well-adapted to deal with tracking problems (Alessio and Bemporad, 2009; Camacho and Bordons, 2007). The success of MPC in several industrial sectors is due to the easy way to formulate the control objective in the time domain and also to the ability to handle constraints (Qin and Badgwell, 2003). A wide variety of applications has been reported in the literature but no application in economics exists to our knowledge. MPC is based on the direct use of an explicit model to predict the future behavior of a process. This model plays a crucial role in the MPC strategy. In our case, the econometric model is used to forecast the behavior of the process (the flow of ES graduates in France) over a finite prediction horizon. In the context of this study, the term "prediction" actually refers to an "anticipation" or "forecast".

The main advantage of this strategy lies in the continuous and systematic nature of its prediction, which enables us to define different time horizons (at the contrary of classic econometrics) and to correct the trajectory continuously thanks to the feedback mechanism of the MPC approach. Another advantage is the fact that this strategy can take into account both estimation errors and modeling errors to correct the reference value at each run. This two-step error correction procedure constitutes a valuable tool towards more robust estimates. Moreover, the MPC approach determines the control inputs exogenously in such a way that it is applied simultaneously to the process and the model. In an econometric model, the effect of the exogenous control input is usually estimated inside the model and is considered as endogenous to the process. For the first time, the control inputs are defined exogenously and policy makers can test an unlimited range of interventions.

The remainder of this paper is organized as follows. Section 2 presents the definition of the employability retained for the CIPEGE tool and the model applied to measure and forecast the French ES graduates' employability. Section 3 deals with the principle of Model Predictive Control and details the control structure used. Section 4 addresses the way of combining the econometric model of employability and the predictive control approach. Then, in section 5, different simulations serve at testing the feasibility of the control strategy. In the last section, we synthesize our preliminary results and draw the perspectives of the proposed approach.

2 Employability

Measuring employability of graduates is a controversial issue due to the difficulty to apply a straightforward definition (Gazier, 1998; McQuaid and Lindsay, 2005; Arjona Perez et al., 2010). Employability is a complex and multi-faceted concept. Therefore, either because of a lack of compatibility between dimensions or a lack of data, a holistic measure of employability has so far been recognized to be impossible. Employability measures are instead reduced to the most pertinent dimensions for the study at hand.

2.1 Definitions

In McQuaid and Lindsay (2005), the authors highlight the existence of two alternative perspectives in the employability debate. One focuses only on the individual's characteristics and skills, referring to the individual's potential to obtain a job. The other perspective takes into account external factors (e.g. labor market institutions, socio-economic status) that influence a person's probability of getting into a job, of moving between jobs or of improving his or her job. In De Grip et al. (2004), these factors are called "effectuation conditions", i.e. the conditions under which workers can effectuate their employability. In addition, the literature also considers the aspects of the time lag between leaving education and employment (Boateng et al., 2011), the degree of skills matched between one's educational background and his or her occupation, and the type of contractual arrangement (full-time vs. part-time; permanent vs. temporary) (Arjona Perez et al., 2010).

Employability is about having the capability to gain initial employment, maintain employment and obtain new employment if required (Cedefop, 2008). In other words, the employability of a graduate is the predisposition of the graduate to exhibit attributes that employers anticipate will be necessary for the effective functioning of their organization (Harvey et al., 1998). Hence, employability is a combination of capacity and willingness to be and to remain attractive for the labor market, for instance, by anticipating changes in tasks and work environment and reacting on them (De Grip et al., 2004). For a given person, employability depends on the knowledge, skills and attitudes he/she possesses, the way he/she uses those assets and presents them to employers (Hillage and Pollard, 1998).

In the context of the CIPEGE tool, we define employability as the capacity of a French Earth Sciences graduate to be employed at a fulfilling job that enables him/her to make use of the skills acquired during the training, given the evolution of the demand of the relevant sectors of activity at the European level.

2.2 Energy prices, environmental policies and employment trends

In a recent report for the European Commissions Employment Directorate General, Cambridge Econometrics (2011) has conducted an in-depth analysis of the employment consequences of the implementation of policies to achieve the key European environmental targets of a 20 percent cut in emissions of greenhouse gases by 2020 (compared to 1990 levels), an increase in the share of renewable energy to 20 percent, and the objective of a 20 percent cut in energy consumption (i.e. the so-called 20-20-20 targets). The findings from that project suggest that after an initial cost to the European Union (EU), the implementation of the EU 20-20-20 targets will lead to a modest positive outcome for GDP growth and employment over the longer term, increasing by around 1-1.15 percent (in net terms) by 2020.

However, when looking at specific industries, these impacts prove to be much differentiated, with some sectors, such as iron, steel, cement and petroleum, experiencing a decrease in employment and sectors, such as renewables, construction and transport, experiencing a growth in jobs by 2020.

The occupations with potential benefits from a low-carbon transition were identified to be Research Development (RD), manufacturing and installation or engineering, operation and maintenance, management, administration and sales.

The shift towards a greater reliance upon renewable energies will create a demand for engineering and technical skills related to generating electricity from wind, marine and solar sources. The forecasts of employment from the E3ME suggest a greater demand for professional, associate professional, and (to a slightly lesser extent) skilled trades workers. Still, these analyses do not go into detail on the implications for specific areas such as science, technology, engineering and mathematics (STEM) (for further details on that topic see, for instance, Wilson et al. (2010)).

Further evidence suggests that the shift towards renewable energies may result in an increasing demand for specific types of engineers and technicians who are not only highly qualified and skilled in their general disciplines, such as electronics engineering, but can also apply their skills within a renewable or green policy environment. Hence, there is likely to be an increasing demand for a form of hybrid skill (the general engineering or technical discipline, plus specific knowledge or experience of renewables) (Cambridge Econometrics, 2011, p.172).

Moreover, there is also an increasing demand for more renewable-specific skills related to hydrology, hydraulics, aerodynamics, ornithology, environmental impact assessment, etc. Both the hybrid and renewable specific skills need to be deployed in a number of functions, including RD, design, operations and maintenance. Although the number of workers required to fill these jobs might be relatively small, they are critical to the success of the renewable sector.

The problem that currently arises in Europe is that there will be potentially more and more markets that will display insufficient capacity to fulfill the demand for these new technologies because of a deficiency of human capital capacity. For example, if Europe is not able to establish economically viable wind turbine or solar panel manufacturing capacity prior to the maturity of the technology and its uptake by users, there is a high risk that non-EU producers will take over the market once established. This would clearly have a negative impact on the overall employment potentials within Europe. Another similar example could be given of innovation in the environmental and eco-technology sector.

Among all European Member States, the United Kingdom (UK) is the only one currently investing in upskilling at tertiary level to meet the new green occupation needs. The main focus of the UK is on the upskilling of tertiary engineering qualifications in energy, especially in installation and maintenance of low-carbon technologies and customer service skills. Another UK training focus is on tertiary qualifications in commodity trader and broker, with the development of practical skills on the functioning of the carbon market and understanding of trading tools. Other EU Member States are instead focusing on the green upskilling of the workforce at the vocational level (e.g., Denmark, Estonia, France and Germany) (GHK, 2010).

2.3 Modeling

Let N_j denote the number of employed individuals in France who are graduated in Earth Sciences at degree level j, with $j \in \{3, 5, 8\}$, such that $j = 3$ corresponds to a 3-year degree (i.e. Bachelor degree); $j = 5$ to a 5-year degree (i.e. Master degree) and $j = 8$ to an 8-year degree (i.e. Ph.D. degree).

For a given degree level j, the number of ES graduates employed at time t is:

$$y_j^F(t) = S_j^F(t) - un_j^F(t) \tag{1}$$

where S_j^F is the stock of ES skills on the French market and un_j^F is the stock of unemployed ES graduates in France.

We model the employment of French ES graduates as a matching function, as suggested by Mortensen and Pissarides (1994), to describe the formation of new relationships ('matches') from unmatched individuals of the appropriate types. In our case, we are interested in the formation of matches, at European level, between the number of unemployed ES j-level graduates and the number of job vacancies in ES domains at j-level. In other terms, we are interested in the European demand for workers with ES skills at each j-level. We assume our matching function to have the following Cobb-Douglas form:

$$m_j^{EU}(t) = M(un_j(t), v_j(t)) = \mu(un_j(t))^a(v_j(t))^b \tag{2}$$

where $m_j^{EU}(t)$ is the number of new matches created at current time t on the European market, and μ, a and b are positive constants. While un_j is now the stock of unemployed ES graduates in Europe, $v_j(t)$ is the number of job vacancies in ES field at degree level j. The matching function is increasing, concave, and homogeneous of degree 1. As reviewed by Petrongolo and Pissarides (2001), the Cobb-Douglas form of the matching function can be justified by empirical evidence of constant returns to scale, i.e. $a + b \approx 1$. If the fraction of workers separating from a firm per period of time (due to firing, quits, and so forth) is δ, then the change in employment from one period to the next is calculated by adding the formation of new matches and subtracting the separation of old matches. Combining equations (1) and (2) yields the following representation of the dynamics of employment over time:

$$y_j^F(t+1) = m_j^{EU}(t) + (1-\delta)y_j^F(t) = \mu(un_j(t))^a(v_j(t))^b + (1-\delta)y_j^F(t) \tag{3}$$

The evolution of unemployment is given by

$$\dot{un}_j = \delta(1 - un_j) - m_j^{EU}(un_j, v_j) \tag{4}$$

Under the assumption that the matching technology[1] exhibits constant returns, this equation has a unique stable steady solution for every vacancy rate v:

$$un_j = \delta/(\delta + m_j^{EU}(v_j/un_j, 1)) = \delta/(\delta + \lambda(\theta)) \tag{5}$$

where $\theta = v_j/un_j$ signals market tightness and $\lambda(\theta) = m_j^{EU}(v_j/un_j, 1)$ represents the unemployment spell hazard. Drawing equation (5) in a vacancy-unemployment space generates a Beveridge curve, i.e. a negative relation between vacancies and unemployment that is convex to the origin by the properties of the matching function (for details see Pissarides and Mortensen, 1999).

Empirical evidence shows that the job destruction flow, δ, is not constant, especially over business cycle frequencies (Davis et al., 1996). Following Pissarides and Mortensen (1999), we therefore allow future job productivity p to vary according to the relative value (in terms of required competences) x of the product or service. Because $x \in [0, 1]$, px can take more than two values[2].

When an unemployed worker and an employer with a vacancy meet, wage bargaining takes place. The outcome is a wage $w(x)$ that divides the quasi-rents associated with a match between worker and employer, according to the value of x. The value of a filled job is a function of the future job productivity, the bargained wage and the probability of destruction of the job. Job creation takes place if all rents from new vacancy creation are exhausted, i.e. if $v_j = 0$. A job is destroyed only if its idiosyncratic productivity falls below a critical level rs (equilibrium reservation productivity), i.e. if $x < rs$.

2.4 Empirical specifications

Except for the matching function, all parameters of the model are estimated, for the years 1990 to 2011, using the annual Employment Survey microdata collected by INSEE (French National Institute of Statistics and Economic Studies).

The matching function m_j^{EU} is estimated using an extended version of the energy-environment-economy model of Europe (E3ME) developed by Cambridge Econometrics to forecast skills supply and demand in Europe (Wilson et al., 2010). Thanks to the structure of the E3ME, m_j^{EU} captures

[1] A matching technology, like a production technology, is a description of the relation between inputs, search and recruiting activity, and the output of the matching process, the flow rate at which unemployed worker and vacant jobs form new job-worker matches (Pissarides and Mortensen, 1999).

[2] According to Pissarides and Mortensen (1999); Mortensen (1994); Cole and Rogerson (1996), the fact of regarding p as a stochastic process characterizing an aggregate shock is consistent with the time series characteristics of job creation and job destruction series reported by Davis et al. (1996).

the influence of international environmental and economic shocks on the demand for skills in Earth sciences.

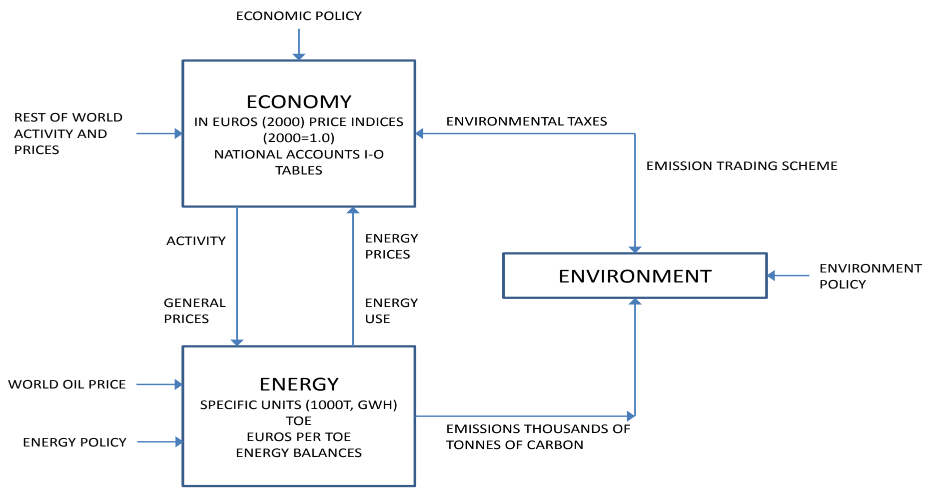

Figure 1: The three dimensions of the E3ME: Energy, Environment and Economy (Source: Cambridge Econometrics, 2011, p.212)

Fig. 1 shows the linkages between the three modules (Energy, Environment and Economy) of the E3ME. Exogenous factors are shown on the outside edge of the chart as inputs into each component. For the European Union (EU) economy, these factors are economic activity and prices in non-EU world areas and economic policy (including tax rates, growth in government expenditures, interest rates and exchange rates). For the energy system, the outside factors are the world oil prices and energy policy (including regulation of energy industries). For the environment component, exogenous factors include policies such as reduction in SO_2 emissions by means of end-of-pipe filters from large combustion plants. The linkages between the modules are shown explicitly by the arrows that indicate which values are transmitted between components. The economic module is solved as an integrated EU regional model, disaggregated at industry and country level. The labor market is treated with sets of equations for employment demand, labor supply, average earnings and hours worked. The equations for labor demand, wages and hours worked are estimated and solved for 42 economic sectors (industries), defined at NACE 2-digit level. Labor participation rates are disaggregated by gender and five-year age bands, and multiplied by Eurostat population data to obtain labor supply.

Employment is modeled using national accounts data, as a total headcount number for each industry and region. This stock is a function of the evolution of unemployment and job vacancies (depending on industry output, wages, hours worked and technological progress) and of global (worldwide) changes in environmental policies and in energy prices and consumption. The industry output is assumed to have a positive effect on employment, while the effect of higher wages and longer working hours is assumed to be negative. The effects of technical progress are ambiguous, as investment may create or replace labor, depending on the sector of activity.

The E3ME model has been extended to include detailed analyses of the skills' demand and supply, as measured by occupation and qualification. Three levels of qualification were defined, namely low (ISCED 0-2), medium (ISCED 3-4) and high (ISCED 5-6). This extended version computes the stock of labor demand by sector, occupation and educational level.

We run the extended E3ME to generate, for the overall European market, the stock of labor demand at the highest level of qualifications (i.e. ISCED 5-6) by sector and level of occupation. Using the annual INSEE Employment Survey (1990-2011), we identify matrices of sectors and occupations that employ workers with a j-level ES degree in France. We merge the E3ME output with the individual data from INSEE on the basis of these matrices and derive the number of demanded ES workers with j-level skills, m_j^{EU}. The current employment of ES graduates in France, $y_j^F(t)$, is estimated by OLS, for each level of degree, using the INSEE microdata, controlling for the age, the gender and the sector of activity. The job destruction flow, λ, is also estimated from the INSEE data. The estimated current matching on the European market is then integrated into equation (3), alongside the current employment level in France $((1-\delta)y_j^F(t))$, to estimate the number of employed j-level ES graduates in France in the next period.

3 Model Predictive Control (MPC)

3.1 Principle

MPC is a mature control strategy. Initially developed for linear systems in the 1970s, MPC had extensively been studied for nonlinear systems with constraints and successfully been applied in numerous industrial domains (Alessio and Bemporad, 2009; Qin and Badgwell, 2003). The MPC strategy is based on the receding horizon principle and is formulated as solving online a nonlinear optimization problem (Camacho and Bordons, 2007). The basic concepts of MPC are the explicit use of a model to predict the process behavior over a finite prediction horizon N_p and the minimization of a cost function with respect to a sequence of N_c controls where N_c is the control horizon. At the current instant k (see Fig. 2), the process output is measured and the MPC algorithm computes a sequence of N_c control inputs by minimizing the tracking error (difference between the reference trajectory and the predicted model output) over N_p. Only the first element of the obtained optimal control sequence is really applied to the process. At the next sampling time (see Fig. 3), the finite prediction horizon moves a step forward, the measurements are updated and the whole procedure is repeated. Given its formulation in an oprtimization problem, MPC is well suited to take into account constraints. Processes are generally subject to constraints on states, inputs or outputs which can easily and explicitly be added to the optimization problem. It is the most effective way to satisfy all kinds of constraints.

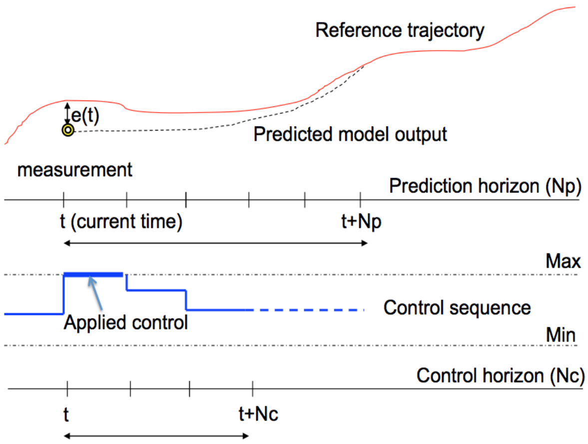

Figure 2: Principle of MPC at the current time t

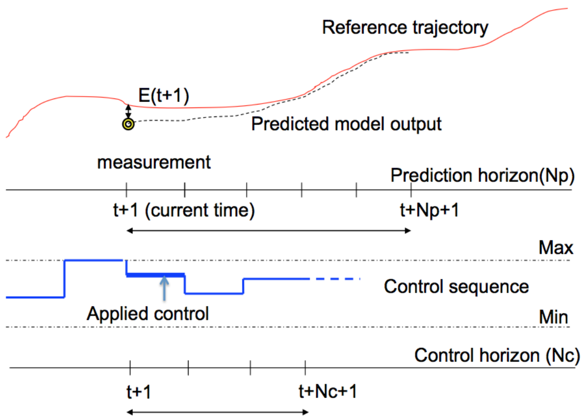

Figure 3: Principle of MPC at the current time $t + 1$

3.2 Internal Model Control (IMC) Structure

Predictions based on data are inevitably subject to disturbances and modeling errors. To gain in robustness, the well-known Internal Model Control (IMC) structure (see Fig. 4) is considered in this approach.

The process (the physical system) is described by its mathematical model. The control inputs u are simultaneously applied to the process and the model. The difference between the process output y_p and the predicted model output y_m provides an error signal e. This signal embeds disturbances and modeling errors and constitutes the feedback information impacting on the reference trajectory y_{ref}. The feedback information is taken into account in an original way rarely used in economics. Due to the sampled data acquisition, a discrete-time formulation is considered where t is the current time iteration.

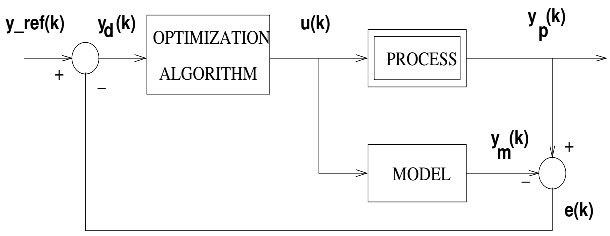

Figure 4: Internal Model Control Structure

According to Fig. 4, we can write:

$$\begin{aligned} y_d(t) &= y_{ref}(t) - e(t) \\ y_d(t) &= y_{ref}(t) - (y_p(t) - y_m(t)) \\ y_d(t) - y_m(t) &= y_{ref}(t) - y_p(t). \end{aligned} \tag{6}$$

The tracking of the reference trajectory y_{ref} by the process output y_p is equivalent to the tracking of the desired trajectory y_d by the model output y_m.

4 Econometric Model-Based Predictive Control

This section addresses the way of combining the econometric model and the MPC approach. The common points to all predictive strategies are discussed according to the control objective: the improvement of French students' employability in the field of ES.

In the context of this study, the term ”prediction” actually refers to an ”anticipation” or ”forecast”.

In the sequel, we show the procedure and the results at the Master degree level, $j = 5$. The same modeling procedures have been performed at the

Bachelor level ($j = 3$) and at the Ph.D. level ($j = 8$) but are not reported here due to space constraints.

4.1 The reference trajectory

The reference trajectory corresponds to the expected behavior of the process. In our case, the reference trajectory y_{ref} to be tracked corresponds to the employability of French ES graduates. This reference has been determined off-line by estimating equations (1), (2) and (3) using E3ME outputs and French microdata (INSEE Employment Survey). The following figure (see Fig. 5) presents the reference trajectory for the employability in France of ES graduates at the Master level, i.e. at level $j = 5$, for the period 2003-2025. While the goodness-of-fit of the reference trajectory for the period 2003-2012 could be tested with observed values of the output variable, the trajectory beyond 2012 was drawn as a linear extrapolation of the previous period. In economics, because of the high degree of unpredictability of individual behaviors, fitted values are likely to variate within a 90 percent confidence interval.

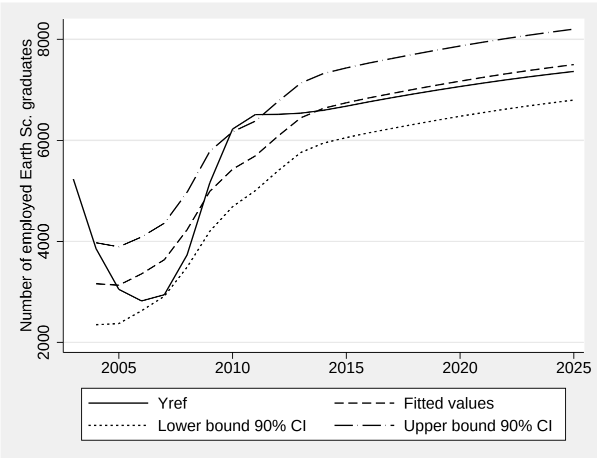

Figure 5: Reference trajectory for the employability in ES at Master degree level

4.2 The model of prediction

The model block, based on an econometric model, will be used to predict, over a finite prediction horizon N_p, the process output y_p describing the measured employability of French graduates in ES.

The model considered is based on a multinomial conditional logit model (McFadden, 1974). Suppose that Y_i represents a discrete choice among J alternatives of studies, including the option of stopping (i.e. exiting the education system or entering the labour market), pursuing in the same major (with different specialization options) or changing major. Let U_{ij} represent the utility function of the j-th choice to the i-th individual. We will treat the U_{ij} as an independent random variable with a systematic component η_{ij} and a random component ε_{ij} such that:

$$U_{ij} = \eta_{ij} + \varepsilon_{ij}. \tag{7}$$

We assume that individuals act in a rational way, maximizing their utility. Thus, subject i will choose alternative j if U_{ij} is the largest of $U_{i1}, ..., U_{iJ}$. The choice has a random component since it depends on random utilities. The probability that subject i will choose alternative j is :

$$\pi_{ij} = Pr[Y_i = j] = Pr[max(U_{i1}, , U_{iJ}) = U_{ij}]. \tag{8}$$

It can be shown that if the error terms ε_{ij} have standard Type I extreme value distributions with density $f(\varepsilon) = exp(-\varepsilon - exp(-\varepsilon))$ then:

$$\pi_{ij} = \frac{exp(\eta_{ij})}{exp(\eta_{ik})}, \tag{9}$$

which is the basic equation defining the multinomial logit model [proof given by Maddala (1983)].
Combining the multinomial and conditional logit formulations, the underlying utilities η_{ij} depend on characteristics of the individuals as well as attributes of the choices, or even variables defined for combinations of individuals and choices (such as an individual's perception of the value of a choice). The general model is usually written as:

$$\eta_{ij} = x_i\beta_j + z_{ij}\gamma. \tag{10}$$

where x_i represents characteristics of the individuals that are constant across choices (e.g., gender) and z_{ij} represents characteristics that vary across choices (e.g., share of theoretical/applied/field work; possibilities to continue further studies; potential employability; etc.). β_j are regression coefficients. Concerning the random component of (eq. 7), we assume that the vector $\varepsilon_i = (\varepsilon_{i1}, ..., \varepsilon iJ)$ has a multivariate normal distribution with mean vector 0 and arbitrary correlation matrix R. The main advantage of this model is that it allows correlation between the utilities that an individual assigns to the various alternatives. Finally, the number of students estimated to choose alternative i is given by:

$$\hat{N}(t) = \sum_{s=1}^{S} w_s P_{si} \tag{11}$$

where P_{si} is the probability (result of eq. 8) that a student in segment s chooses alternative i and w_s is the number of students enrolled in segment s.

For control purposes, the model is written and identified under a state-space representation. For the Bachelor graduates, it yields:

$$\begin{pmatrix} \hat{N}_3(t) \\ \hat{N}_2(t) \\ \hat{N}_1(t) \end{pmatrix} = \begin{pmatrix} r_3 & a & 0 \\ 0 & r_2 & b \\ 0 & 0 & r_1 \end{pmatrix} \begin{pmatrix} \hat{N}_3(t-1) \\ \hat{N}_2(t-1) \\ \hat{N}_1(t-1) \end{pmatrix} + \begin{pmatrix} 0 & 0 & c \\ 0 & d & 0 \\ f & 0 & 0 \end{pmatrix} \begin{pmatrix} u(t) \\ u(t-1) \\ u(t-2) \end{pmatrix} \tag{12}$$

$\hat{N}_j$ represents the potential (or estimated) number of students who have completed level $j = 1, 2, 3$. The control input $\tilde{u}$ is the number of students enrolled at time t and $t-2$, at level $j = 1$. The diagonal coefficients r_j are the repetition rate at level j.

For the Bachelor graduates that pursue to a Master degree, the model proceeds as follows:

$$\begin{pmatrix} \hat{N}_5(t) \\ \hat{N}_4(t) \end{pmatrix} = \begin{pmatrix} r_5 & a \\ r_4 & b \end{pmatrix} \begin{pmatrix} \hat{N}_5(t-1) \\ \hat{N}_4(t-1) \end{pmatrix} + \begin{pmatrix} 0 & g \\ h & 0 \end{pmatrix} \begin{pmatrix} u(t) \\ u(t-1) \end{pmatrix} \tag{13}$$

4.3 The cost function (optimization criterium)

It is usually a quadratic function of the tracking error. The error signal e over the prediction horizon is computed thanks to a linear interpolation over the past measured errors, and it is updated at each measurement. Since the reference y_{ref} is known over the whole working horizon, the desired trajectory can be computed:

$$y_d(k) = y_{ref}(k) - e(k), \ k \in [t+1, t+N_p], \tag{14}$$

and the cost function can be written in discrete-time as:

$$J(u) = \textstyle\sum_{k=t+1}^{t+N_p} e_{tra}(k)^T Q \ e_{tra}(k) + \Delta u(k-1)^T R \ \Delta u(k-1) \tag{15}$$

where $e_{tra} = y_d - y_m$, Q and R are symmetric definite positive matrices and $\Delta u(k-1) = u(k-1) - u(k-2)$.

4.4 The solving optimization method

The cost function J is to be minimized with respect to a sequence of N_c different controls noted $\tilde{u} = \{u(t), u(t+1), ..., u(t+N_c), ..., u(t+N_p-1)\}$ where N_c is the control horizon ($N_c < N_p$). From $u(t+N_c+1)$ to $u(t+N_p-1)$, the inputs are constant and equal to $u(t+N_c)$. The mathematical formulation of MPC is then given by the following optimization problem:

$$\min_{\tilde{u}} \ J(u). \tag{16}$$

Although the prediction and optimization steps are performed over the prediction horizon, only the value of the input for the current time $u(t)$ is really applied to the process.

5 Simulations

All the presented simulations are performed with Matlab software. The constrained optimization problem is solved by using the Matlab function $fmincon$.

5.1 Data and modeling

The internal model uses data from a student tracking survey collected by the Students' Life Observatory (OVE), which describes the transition trajectories of Master graduates 3 years after graduation, by degree field; university administrative records of the number of intakes and graduates, per year; and complementary data from the report by Varet (2008).

The data collected are represented in Fig. 6. As explained in section 4.1, the reference trajectory is calculated using INSEE and E3ME data. The inputs (i.e. number of students enrolled in ES training and completion rate) are obtained from the OVE data and the administrative data. Thanks to an identification procedure, we obtained a model which matches the process with a relative error of 9.33% (see Fig. 7).

As can be seen, the trajectory of the measured employability is remarkably non-linear. The significant increase in the number of employed ES graduates with a Master degree between 2008 and 2009 is due to the reform of the university system launched in 2004-2005 in relation to the European Bologna Process. That reform harmonized the university degrees across Europe into a three-level structure: Bachelor-Master-PhD. In France, this new structure has replaced the previous five-level structure (DEUG-Licence-Matrise-DEA/DESS-Doctorat). The former Matrise degree corresponds to a Master I level and the former DEA/DESS degree to a Master II. The reform of 2004 affected essentially the students who enrolled in their first year at university in 2004-2005. Among that students cohort, we observe a significant increase in the number of graduates at the level $j = 5$ due to the abolition of the $j = 4$ degree (namely, the Matrise).

Over the period 2004-2012, the three main sectors of activities employing Master-degree ES graduates were education, professional services and public administration and defence. While ES graduates used to have a relative high probability of being employed in the sector of mechanical engineering before 2008; with the crisis, their chances of employment have decreased in that sector. Instead, we observe an increase in the number of employed ES graduates in the service sector, largely correlated to a global inflation in consultancy jobs and fixed-term contracts since 2008 (Cutuli and Guetto, 2013; Oliver, 2012; O'Connor, 2013).

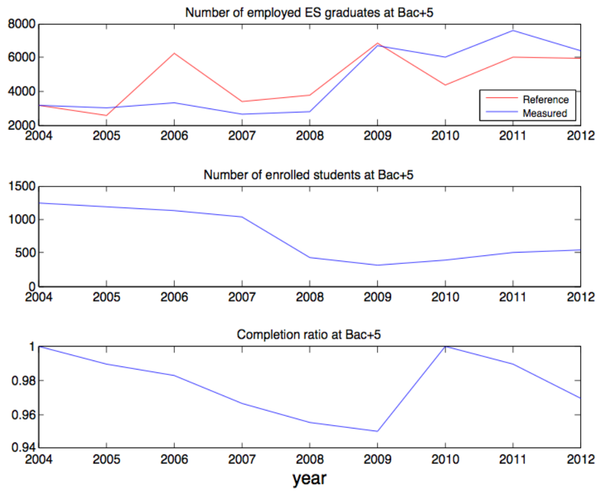

Figure 6: Reference and measured employability in ES at Master degree level

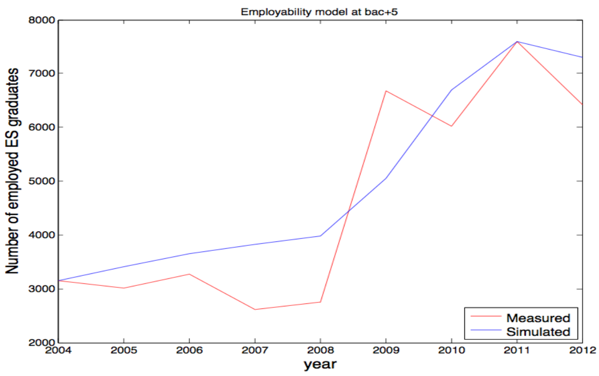

Figure 7: Model of the employability in ES at Master degree level

5.2 Predictive Control

The econometric model-based predictive control described in section 4 is implemented. The simulation was performed under the following conditions: $N_p = 5$, $N_c = 4$, $R = [10; 0.1]$ and $Q(j) = Q(1)^j$ with $Q(1) = 2$. The future tracking errors are more and more weighted in order to give importance to the final objective, i.e. the desired employability at the end of the prediction horizon, and this, at each sampling time. The reference employability is still obtained applying the model described in section 2.3, using INSEE and E3ME data. Several simulations were carried out according to different horizons of control and prediction. The prediction horizon $N_p = 5$ seems to be the best compromise between the tracking accuracy, the intrinsic dynamic (the current control will impact the employability of Master degree graduates in at least five years) and the stability of the controlled system.

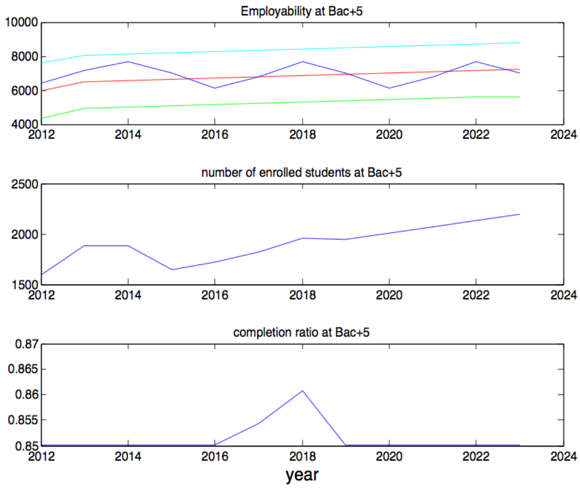

Figure 8: Employability in ES at Master degree level: 2013-2023

From Fig. 8, we can see that the process output tracks the reference trajectory by remaining within the range of uncertainty. The completion ratio is not a very sensitive variable control. In future works, we will evaluate if this input is really relevant. On the other hand, the number of students enrolled seems more relevant and gives a valuable information to policy makers to anticipate universities' future adjustments in human and physical resources. If more students' intakes are needed to reach the desired employability levels, then universities will need to ensure that they have the capacity to welcome and train efficiently this large influx of students.

Overall, these simulations show that the application of the approach of predictive control to economic issues is feasible and can lead to potentially useful results from a social, educational and economic point of view.

6 Conclusions

This paper presented an innovative tool to predict the employability of French graduates in Earth Sciences. Rather than formulating this control objective as a classic computational general equilibrium (CGE) problem, it has been formulated as an optimization problem. For the first time, Model Predictive Control was combined with an econometric model of employability. The MPC enables to take into account disturbances and modeling errors through an internal model control, which complements efficiently the error correction model (ECM) implemented in the econometric model used to measure the reference trajectory. Moreover, combining the econometrics approach and the MPC yields a predictive tool where the control inputs are held exogenous to the optimization process, which makes it possible to test an unlimited range of possible interventions. The calculated control inputs can then serve as potential action-tools for policy makers. Furthermore, because this approach is very flexible, it can easily be adapted to other disciplines (chemistry, medicine, ...) but also to other countries. Hence, the statistical capacity (in terms of error control), the economic relevance (in terms of control inputs formulation) and the unlimited potentialities for application expansions of the CIPEGE tool, makes it an attractive and valuable decision tool for universities and policy makers.

As with any approach of predictive control, the model is the cornerstone of the strategy and needs to be clearly identified from consistent data.

At this early stage of the project, the results obtained from different simulations are very encouraging. Additional data should improve the model and, thus, the tracking accuracy of the reference employability.

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