

# A priori convergence of the Generalized Empirical Interpolation Method.

Yvon Maday, Olga Mula, Gabriel Turinici

#### ▶ To cite this version:

Yvon Maday, Olga Mula, Gabriel Turinici. A priori convergence of the Generalized Empirical Interpolation Method.. 2013. hal-00797271v2

### HAL Id: hal-00797271 https://hal.sorbonne-universite.fr/hal-00797271v2

Preprint submitted on 8 Mar 2013 (v2), last revised 23 Nov 2013 (v3)

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

## A priori convergence of the Generalized Empirical Interpolation Method

Yvon Maday UPMC Univ Paris 06, UMR 7598, Laboratoire Jacques-Louis Lions, F-75005, Paris, France. and Institut Universitaire de France and Division of Applied Mathematics, Brown University, Providence RI, USA.

Email: maday@ann.jussieu.fr

Olga Mula CEA Saclay, DEN/DANS/DM2S/SERMA/LLPR

Email: olga.mulahernandez@cea.fr

Gabriel Turinici **CEREMADE** 

Universite Paris Dauphine 91191 Gif-Sur-Yvette CEDEX - France Place du Marechal de Lattre de Tassigny 75016 Paris, France

Email: Gabriel.Turinici@dauphine.fr

Abstract—In an effort to extend the classical lagrangian interpolation tools, new interpolating methods that use general interpolating functions are explored. The Generalized Empirical Interpolation Method (GEIM) belongs to this class of new techniques. It generalizes the plain Empirical Interpolation Method [1] by replacing the evaluation at interpolating points by application of a class of interpolating linear functions. Since its efficiency depends critically on the choice of the interpolating functions (that are chosen by a Greedy selection procedure), the purpose of this paper is therefore to provide a priori convergence rates for the Greedy algorithm that is used to build the GEIM interpolating spaces.

#### I. INTRODUCTION

The extension of the lagrangian interpolation process is an old problem that is still currently subject to an active research (see, e.g. [1] and also the activity concerning the kriging [2], [3] in the stochastic community). While this classical method approximates general functions by finite sums of well chosen, linearly independent interpolating functions (e.g. polynomial functions) and the optimal location of the interpolating points is well documented (and completely solved in one dimension), the question remains on how to approximate general functions by finite expansions involving general interpolating functions and how to optimally select the interpolation points in this

One step in this direction is the Empirical Interpolation Method (EIM, [4], [5], [1]) that has been developed in the broad framework where the functions f to approximate belong to a compact set F of a Banach space  $\mathcal{X}$ . The structure of F is supposed to make any  $f \in F$  be approximable by finite expansions of small size. In particular, this is the case when the Kolmogorov n-width of F in  $\mathcal{X}$  is small. Indeed, the Kolmogorov n-width of F in  $\mathcal{X}$  is defined by  $\inf_{\substack{X_n\subset \mathcal{X}\\\dim(X_n)=n}}\sup_{x\in F}\inf_{y\in X_n}\|x-y\|_{\mathcal{X}} \text{ (see [6]) and }$  $d_n(F,\mathcal{X}) :=$ 

measures the extent to which F can be approximated by some finite dimensional space  $X_n \subset \mathcal{X}$  of dimension n. The Empirical Interpolation Method builds simultaneously the set of interpolating functions and the associated interpolating points by a greedy selection procedure (see [4]).

A recent generalization of this interpolation process consists in replacing the evaluation at interpolating points by application of a class of interpolating continuous linear functions chosen in a given dictionary  $\Sigma \subset \mathcal{L}(F)$  and this gives rise to the so-called Generalized Empirical Interpolation Method (GEIM, [7]). In this newly developed method, the particular case where the space  $\mathcal{X} = L^2(\Omega)$  is considered, with  $\Omega$  being a bounded spacial domain of  $\mathbb{R}^d$  and F being a compact set of  $L^2(\Omega)$ .

In the present work, we analyze the quality of the finite dimensional subspaces  $X_n \subset F$  built by the greedy selection procedure of GEIM together with the properties of the associated interpolation operator. For this purpose, the accuracy of the approximation in  $X_n$  of the elements of Fwill be compared to the best possible performance which is the Kolmogorov n- width  $d_n(F, L^2(\Omega))$ .

The proceeding is organized as follows: after a brief recall of GEIM's Greedy algorithm (section II), we will analyze in sections III and IV some convergence decay rates of the generalized empirical interpolation error as the dimension nof  $X_n$  increases and when  $d_n(F, L^2(\Omega))$  has a polynomial or an exponential decreasing behavior.

#### II. THE GENERALIZED EMPIRICAL INTERPOLATION **METHOD**

In a similar procedure as in the Empirical Interpolation Method (EIM) [4], [5], [1], the Generalized EIM allows to define simultaneously the set of interpolating functions recursively chosen in F together with the associated linear functions selected from a dictionary of continuous linear forms  $\Sigma \subset \mathcal{L}(F)$ , with norm 1 in  $L^2(\Omega)$ . The dictionary has the additional property that if  $\varphi \in F$  is such that  $\sigma(\varphi) = 0$  for any  $\sigma \in \Sigma$ , then  $\varphi = 0$ . The selection of the interpolating functions and linear forms is based on a greedy selection procedure as outlined in [7].

The first interpolating function is, e.g.:

$$\varphi_0 = \arg \sup_{\varphi \in F} \|\varphi\|_{L^2(\Omega)},$$

the first interpolating linear form is:

$$\sigma_0 = arg \sup_{\sigma \in \Sigma} |\sigma(\varphi_0)|.$$

We then define the first basis function as:  $q_0 = \frac{\varphi_0}{\sigma_0(\varphi_0)}$ . The second interpolating function is:

$$\varphi_1 = \arg \sup_{\varphi \in F} \|\varphi - \sigma_0(\varphi)q_0\|_{L^2(\Omega)}.$$

The second interpolating linear form is:

$$\sigma_1 = arg \sup_{\sigma \in \Sigma} |\sigma(\varphi_1 - \sigma_0(\varphi_1)q_0)|,$$

and the second basis function is defined as:

$$q_1 = \frac{\varphi_1 - \sigma_0(\varphi_1)q_0}{\sigma_1(\varphi_1 - \sigma_0(\varphi_1)q_0)},$$

we then proceed by induction: assuming that we have built the set of interpolating functions  $\{q_0, q_1, \dots, q_{N-1}\}$  and the set of associated interpolating linear forms  $\{\sigma_0, \sigma_1, \dots, \sigma_{N-1}\}\$ , for  $N \geq 1$ , we first solve the interpolation problem : find  $\{\alpha_i^N(\varphi)\}_j$  such that

$$\forall i = 0, \dots, N-1, \quad \sigma_i(\varphi) = \sum_{j=0}^{N-1} \alpha_j^N(\varphi)\sigma_i(q_j),$$

and then compute:

$$\mathcal{J}_N[\varphi] = \sum_{j=0}^{N-1} \alpha_j^N(\varphi) q_j$$

We then evaluate

$$\forall \varphi \in F, \quad \varepsilon_N(\varphi) = \|\varphi - \mathcal{J}_N[\varphi]\|_{L^2(\Omega)},$$

and define:

$$\varphi_N = arg \sup_{\varphi \in F} \varepsilon_N(\varphi)$$

and:  $\sigma_N = \underset{\sigma \in \Sigma}{arg \ sup} |\sigma(\varphi_N - \mathcal{J}_N[\varphi_N])|$ . The next basis function is then

$$q_N = \frac{\varphi_N - \mathcal{J}_N[\varphi_N]}{\sigma_N(\varphi_N - \mathcal{J}_N[\varphi_N])}.$$

We finally set  $X_{N+1} \equiv \operatorname{span} \{q_j, j \in [0, N]\} =$ span  $\{\varphi_j, j \in [0, N]\}$ . It has been proven in [7]:

Lemma 1: For any N, the set  $\{q_i, j \in [0, N-1]\}$  is linearly independent and  $X_N$  is of dimension N. The generalized empirical interpolation procedure is well-posed in  $L^2(\Omega)$  and  $\forall \varphi \in F$ , the interpolation error satisfies:

$$\|\varphi - \mathcal{J}_N[\varphi]\|_{L^2(\Omega)} \le (1 + \Lambda_N) \inf_{\psi_N \in X_N} \|\varphi - \psi_N\|_{L^2(\Omega)}$$

where  $\Lambda_N$  is the Lebesgue constant in the  $L^2$  norm:  $\Lambda_N :=$  $\sup_{\varphi \in F} \frac{\|\mathcal{J}_N[\varphi]\|_{L^2(\Omega)}}{\|\varphi\|_{L^2(\Omega)}}$ 

#### III. Preliminary notations and basic properties

In what follows, we denote by  $(\varphi_n^*)_{n\geq 0}$  the orthonormal system obtained from  $(\varphi_n)_{n\geq 0}$  by Gram-Schmidt orthogonal-

For any  $n \ge 1$ , we define the orthogonal projector  $P_n$  from  $\mathcal{X}$  onto  $X_n$  which is given by  $P_n(f) = \sum_{j=0}^{n-1} \langle f, \varphi_j^* \rangle \varphi_j^*$ ,  $\forall f \in F$ , where < ... > is the  $L^2(\Omega)$  scalar product. In particular:  $\varphi_n = P_{n+1}(\varphi_n) = \sum_{j=0}^n a_{n,j} \varphi_j^*$ , with  $a_{n,j} := <$  $\varphi_n, \varphi_j^* > 0 \le j \le n.$ 

Finally, let us denote as  $\tau_0(F)_{L^2(\Omega)} := d_0(F, L^2(\Omega))$  and, for any  $n \geq 1$ :  $\tau_n := \tau_n(F)_{L^2(\Omega)} := \max_{f \in F} \|f - P_n(f)\|_{L^2(\Omega)}$  and by  $\gamma_n$  the constant  $\gamma_n = 1/(1+\Lambda_n)$ . With these notations Lemma 1 states

$$\forall \varphi \in F, \quad \gamma_n \|\varphi - \mathcal{J}_N[\varphi]\|_{L^2(\Omega)} \le \tau_n. \tag{1}$$

We begin by proving the two following lemmas:

Lemma 2: For any  $n \geq 1$ ,  $\|\varphi_n - P_n(\varphi_n)\|_{L^2(\Omega)} \geq$  $\gamma_n \tau_n(F)$ .

*Proof:* From (1) applied to  $\varphi = \varphi_n$  we have  $\|\varphi_n - \varphi_n\| = 1$  $P_n(\varphi_n)\|_{L^2(\Omega)} \geq \gamma_n \|\varphi_n - \mathcal{J}_n(\varphi_n)\|_{L^2(\Omega)}$ . But  $\|\varphi_n - \mathcal{J}_n(\varphi_n)\|_{L^2(\Omega)}$  $\mathcal{J}_n(\varphi_n)\|_{L^2(\Omega)} \ge \|\varphi - \mathcal{J}_n(\varphi)\|_{L^2(\Omega)}$  for any  $\varphi \in F$  according to the definition of  $\varphi_n$ . Thus  $\|\varphi_n - P_n(\varphi_n)\|_{L^2(\Omega)} \ge \gamma_n \|\varphi - \varphi_n\|_{L^2(\Omega)}$  $\mathcal{J}_n(\varphi)\|_{L^2(\Omega)} \ge \gamma_n \|\varphi - P_n(\varphi)\|_{L^2(\Omega)}.$ 

Lemma 3: Let A be the lower triangular matrix defined by  $A := (a_{i,j})_{i,j=0}^{\infty} (a_{i,j} := 0, j > i)$ . A has two important properties:

- P1:  $\gamma_n \tau_n \leq |a_{n,n}| \leq \tau_n$ . P2: For every  $m \geq n$ ,  $\sum_{n=0}^{\infty} a_{m,j}^2 \leq \tau_n^2$ .
- P1:  $\forall f \in F$ :  $P_n(f) = \sum_{j=0}^{n-1} \langle f, \varphi_j^* \rangle \varphi_j^*$ . In particular:  $\varphi_n - P_n(\varphi_n) = a_{n,n} \varphi_n^* \Rightarrow \|\varphi_n - P_n(\varphi_n)\|_{L^2(\Omega)}^2 = a_{n,n}^2$ . The upper bound is thus obvious and Lemma 2 gives the lower bound.
- P2: For every  $m \geq n$ :  $\sum_{j=n}^{m} |a_{m,j}|^2 = \|\varphi_m \varphi_m\|$  $P_n(\varphi_m)\|_{L^2(\Omega)}^2 \le \max_{f \in F} \|f - P_n(f)\|^2 = \tau_n^2.$

#### IV. A PRIORI CONVERGENCE RATES OF THE GEIM **GREEDY METHOD**

In order to get convergence decay rates in the generalized interpolation error of our method, we first note that lemma 2 shows that the GEIM's Greedy algorithm is what is called in [8] a "weak Greedy algorithm" of parameter  $\gamma_n = 1/(1+\Lambda_n)$ that depends on the dimension of  $X_n$ .

Thanks to this observation, to get the desired result, convergence decay rates in the sequence  $(\tau_n)_{n>0}$  will first be derived. This task consists in extending the proofs of [8] where the constant case  $\gamma_n = \gamma$  was addressed and where the following two results were proven in Corollary 3.3:

i) If 
$$d_n(F) \leq C_0 n^{-\alpha}$$
 for  $n \geq 1$ , then  $\tau_n \leq C_0 2^{5\alpha+1} \gamma^{-2} n^{-\alpha}$  for  $n \geq 1$ .

$$\begin{array}{lll} \text{i)} & \text{If} & d_n(F) \leq C_0 n^{-\alpha} \; \; \text{for} \; \; n \geq 1, \; \; \text{then} \; \; \tau_n \leq \\ & C_0 2^{5\alpha+1} \gamma^{-2} n^{-\alpha} \; \; \text{for} \; \; n \geq 1. \\ & \text{ii)} & \text{If} \; \; d_n(F) \leq C_0 e^{-c_0 n^{\alpha}} \; \; \text{for} \; \; n \geq 1, \; \text{then} \; \; \tau_n \leq \\ & \sqrt{2C_0} \gamma^{-1} e^{-c_1 n^{\alpha}} \; \; \text{for} \; \; n \geq 1, \; \text{where} \; c_1 := 2^{-1-2\alpha} c_0. \end{array}$$

In order to extend i) and ii) to the more general case where  $\gamma$  depends on the dimension n, the following preliminary theorem is required:

Theorem 4: For any  $N \geq 0$ , let us consider the weak Greedy algorithm with constant  $\gamma_N$  in  $L^2(\Omega)$  associated with the compact set F, we have the following inequalities between  $\tau_N$  and  $d_N := d_N(F, L^2(\Omega))$ : for any  $K \ge 1, 1 \le m < K$ 

$$\prod_{i=1}^{K} \tau_{N+i}^2 \le \frac{1}{\prod\limits_{i=1}^{K} \gamma_{N+i}^2} \left(\frac{K}{m}\right)^m \left(\frac{K}{K-m}\right)^{K-m} \tau_{N+1}^{2m} d_m^{2(K-m)}.$$

*Proof:* This result is an extension of Theorem 3.2 of [8] to the case where the parameter of the weak Greedy algorithm  $(\gamma_N)$  depends on the dimension of the reduced space  $X_N$ . Its proof is a slight modification to the one provided in [8] using  $\gamma_N$  and the properties P1 and P2 stated in Lemma 3.

Using theorem 4, convergence rates in the sequence  $(\tau_n)_{n\geq 0}$ when  $(d_n)_{n\geq 0}$  has a polynomial or an exponential decay can be inferred and lead to lemmas 5 and 6:

Lemma 5 (Polynomial decay of  $(d_n)_{n\geq 0}$ ): For any  $n\geq 1$ , let  $n = 4\ell + k$  (where  $\ell \in \{0, 1, ...\}$  and  $k \in \{0, 1, 2, 3\}$ ). Assume that there exists a constant  $C_0 > 0$  such that  $\forall n \geq 1$ ,  $d_n(F, L^2(\Omega)) \leq C_0 n^{-\alpha}, \text{ then } \tau_n \leq C_0 \beta_n n^{-\alpha}, \text{ where } \beta_1 = 2$  and for  $n \geq 2$ :  $\beta_n = \beta_{4\ell+k} := \sqrt{2\beta_{\ell_1}} \frac{1}{\prod_{i=1}^{\ell_2} \gamma_{\ell_1 - \lceil \frac{k}{4} \rceil + i}^{\frac{1}{\ell_2}}} (2\sqrt{2})^{\alpha}$ 

and 
$$\ell_1 = 2\ell + \lfloor \frac{2k}{3} \rfloor$$
,  $\ell_2 = 2\left(\ell + \lceil \frac{k}{4} \rceil\right)$ .

The proof is done by recurrence over n. We initialize the reasoning by proving that  $\tau_1 \leq 2C_0$  and then prove the general statement for  $n \geq 2$ .

Case n=1: We recall that  $\varphi_0=\arg\sup_{\varphi\in F}\|\varphi\|_{L^2(\Omega)}$ and that  $P_1$  is the projector operator onto  $span\{\varphi_0\}$ . We set:  $f_1 = arg \ \tau_1 = arg \ \max_{f \in F} \|f - P_1(f)\|_{L^2(\Omega)}$  and let  $\mu \in F$  span the one dimensional subspace of F for which  $d_1 \geq \|f - P_{\mu}(f)\|_{L^2(\Omega)}$  for any  $f \in F$  ( $P_{\mu}$  being the projector operator onto  $span\{\mu\}$ ). We have:  $\tau_1 = ||f_1||$  $P_1(f_1)\|_{L^2(\Omega)} = \|f_1 - P_{\mu}(f_1) + P_{\mu}(f_1) - P_1(f_1)\|_{L^2(\Omega)} = \|f_1 - P_{\mu}(f_1)\|_{L^2(\Omega)} = \|f_1 - P_{\mu}(f_1)\|_$  $||f_1 - P_{\mu}(f_1) - P_1(f_1 - P_{\mu}(f_1)) + P_{\mu}(f_1) - P_1 P_{\mu}(f_1)||_{L^2(\Omega)} \le$  $d_1 + ||P_{\mu}(f_1) - P_1 P_{\mu}(f_1)||_{L^2(\Omega)}.$ 

We have: 
$$\|P_{\mu}(f_1) - P_1 P_{\mu}(f_1)\|_{L^2(\Omega)} = \|\frac{\langle f_1, \mu \rangle \mu}{\|\mu\|_{L^2(\Omega)}^2} - \frac{\langle \langle f_1, \mu \rangle \mu, \varphi_0 \rangle \varphi_0}{\|\mu\|_{L^2(\Omega)}^2 \|\varphi_0\|_{L^2(\Omega)}^2} \|_{L^2(\Omega)} = \frac{|\langle f_1, \mu \rangle|}{\|\mu\|_{L^2(\Omega)}} \|\frac{\mu}{\|\mu\|_{L^2(\Omega)}} - \frac{\langle \varphi_0, \mu \rangle \varphi_0}{\|\mu\|_{L^2(\Omega)}} \|_{L^2(\Omega)}.$$

Since for any  $x,y \in F$  with norm 1 we have  $||x-| < x, y > y||_{L^2(\Omega)} = ||y-| < x, y > x||_{L^2(\Omega)},$ we deduce that :  $||P_{\mu}(f_1)|| - |P_1P_{\mu}(f_1)||_{L^2(\Omega)}$ 

$$\begin{split} & \frac{|< f_1, \mu>|}{\|\mu\|_{L^2(\Omega)}} \|\frac{\varphi_0}{\|\varphi_0\|_{L^2(\Omega)}} - \frac{<\varphi_0, \mu>\mu}{\|\mu\|_{L^2(\Omega)}^2 \|\varphi_0\|_{L^2(\Omega)}} \|_{L^2(\Omega)}. \\ & \text{Hence:} \quad \tau_1 & \leq \quad d_1 \ + \ \frac{|< f_1, \mu>|}{\|\mu\|_{L^2(\Omega)} \|\varphi_0\|_{L^2(\Omega)}} \|\varphi_0 \ - \\ & \frac{<\varphi_0, \mu>\mu}{\|\mu\|_{L^2(\Omega)}^2} \|_{L^2(\Omega)} \leq d_1 \left(1 + \frac{|< f_1, \mu>|}{\|\mu\|_{L^2(\Omega)} \|\varphi_0\|_{L^2(\Omega)}}\right) \leq 2d_1. \end{split}$$

Remark 1: In the case where  $\|\varphi_0\|_{L^2(\Omega)} \ge \gamma_0 \|f\|_{L^2(\Omega)}$  for any  $f \in F$  (0 <  $\gamma_0 \le 1$ ), we would have obtained  $\tau_1 \le$  $d_1\left(1+\frac{1}{\gamma_0}\right)$ .

Case  $n \geq 2$ : Let n = N + K for any  $N \geq 0$ ,  $K \geq 2$ . If  $i \leq K$ , we have  $\tau_n = \tau_{N+K} \leq \tau_{N+i}$ from the monotonicity of  $(\tau_n)_{n\geq 0}$ . By combining this inequality and theorem 4, if  $1 \leq m < K$ , we derive

that 
$$\tau_n \leq \frac{1}{\prod\limits_{k=1}^K \gamma_{N+i}^{\frac{1}{K}}} \sqrt{\left(\frac{K}{m}\right)^{\frac{m}{K}} \left(\frac{K}{K-m}\right)^{1-\frac{m}{K}}} \tau_{N+1}^{\frac{m}{K}} d_m^{1-\frac{m}{K}} \leq$$

$$\frac{1}{\prod\limits_{i=1}^{K} \gamma_{N+i}^{\frac{1}{K}}} \sqrt{2} \tau_{N+1}^{\frac{m}{K}} d_m^{1-\frac{m}{K}}, \text{ since } x^{-x} (1-x)^{x-1} \leq 2 \text{ for any } x, \\ \prod\limits_{i=1}^{K} \gamma_{N+i}^{\frac{1}{K}} \\ 0 < x < 1. \text{ We now use that } d_m \leq C_0 m^{-\alpha} \text{ and the recurrence}$$

hypothesis in  $N+1 < n : \tau_{N+1} \le C_0 \beta_{N+1} (N+1)^{-\alpha}$  which yield:  $\tau_{N+K} \leq C_0\sqrt{2}\frac{1}{K} \gamma_{N+1}^{\frac{1}{K}} \beta_{N+1}^{\frac{m}{K}} \xi(n)^{\alpha} (N+K)^{-\alpha}$  where  $\xi(n) = \frac{n}{m} \left(\frac{m}{N+1}\right)^{\frac{1}{K}} .$ 

$$\xi(n) = \frac{n}{m} \left( \frac{m}{N+1} \right)^{\frac{i}{m}}.$$

Any  $n \ge 2$  can be written as  $n = 4\ell + k$  with  $\ell \in \{0, 1, \dots\}$ and  $k \in \{0, 1, 2, 3\}$ . If k = 1, 2 or 3, it can easily be proven that  $\xi(n) \leq 2\sqrt{2}$  by setting  $N = 2\ell - 1$ ,  $K = 2\ell + 2$ ,  $m = 2\ell + 2$  $\ell + 1$  if k = 1 and  $\ell > 1$ ,  $N = 2\ell$ ,  $K = 2\ell + 2$ ,  $m = \ell + 1$ if k=2 and  $\ell \geq 0$  and  $N=2\ell+1, \ K=2\ell+2, \ m=\ell+1$ if k=3 and  $\ell \geq 0$ . These choices of N, K and m combined with the upper bound of  $\xi$  yield the result  $\tau_n \leq C_0 \beta_n n^{-\alpha}$  in the case k = 1, 2 or 3.

In the case  $n=4\ell$  ( $\ell\geq 1$ ), using the fact that  $\tau_{N+1}\leq \tau_N$ , we can derive that  $\tau_n \leq \frac{1}{\frac{K}{K} \gamma_{N+i}^{\frac{1}{K}}} \sqrt{2} \tau_N^{\frac{m}{K}} d_m^{1-\frac{m}{K}}$ . If we choose

 $N=K=2\ell$  and  $m=\ell,$  the previous inequality directly yields  $au_{4\ell} \leq C_0\sqrt{2eta_{2\ell}} \frac{1}{\sum\limits_{i=1}^{2\ell} \gamma_{2\ell+i}^{\frac{1}{2\ell}}} (2\sqrt{2})^{\alpha} (4\ell)^{-\alpha}.$ 

Lemma 6 (Exponential decay in  $(d_n)_{n>0}$ ): Assume that there exists a constant  $C_0 > 0$  such that  $\forall n \geq 1$ , where  $\beta_n:=\frac{1}{\prod\limits_{i=1}^{n}\gamma_{\lfloor\frac{n}{2}\rfloor+i}^{\frac{1}{\lfloor\frac{n}{2}\rfloor}}}\sqrt{2\beta_{\lfloor\frac{n}{2}\rfloor}}$  for  $n\geq 2$ ,  $\beta_1=2$  and

*Proof:* The proof is done by recurrence over n. The case n = 1 is addressed by following the same lines as in lemma 5.

In the case n=2, we have:  $\tau_2 \leq \tau_1 \leq 2C_0$ .

For  $n\geq 3$ , we start from  $\tau_{N+K}\leq \frac{1}{\prod\limits_{i=1}^K \gamma_{N+i}^{\frac{1}{K}}}\sqrt{2}\tau_{N+1}^{\frac{m}{K}}d_m^{1-\frac{m}{K}}$ 

and treat the cases  $n=N+K=2\ell$  and  $n=N+K=2\ell+1$ separately  $(\ell \geq 1)$ .

If  $n=N+K=2\ell$ , we choose  $N=K=\ell$  and  $m=\lfloor\frac{K}{2}\rfloor$ . The inequality yields  $\tau_{2\ell} \leq \frac{1}{\prod\limits_{\ell=1}^{\ell} \gamma_{\ell+i}^{\frac{1}{\ell}}} \sqrt{2\tau_{\ell}} e^{-c_2(2\ell)^{\alpha}}$ .

In a similar procedure, the desired result can be inferred for  $n = N + K = 2\ell + 1$  if we choose  $N = \ell$ ,  $K = \ell + 1$  and  $m = \lfloor \frac{K}{2} \rfloor$ .

- Remark 2: 1) In the case where  $\gamma_n$  is constant  $\gamma_n = \gamma$ , lemmas 5 and 6 yield results that are similar to the ones obtained in [8] (see i) and ii) of this proceeding).
- 2) In the case where  $(\gamma_n)_{n>1}$  is a monotonically decreasing sequence, the following bounds can be derived for  $\tau_n$ :

  - If  $d_n(F, L^2(\Omega)) \leq C_0 n^{-\alpha}$  for any  $n \geq 1$ , then  $\tau_n \leq C_0 \beta n^{-\alpha}$  for  $n \geq 1$ , with  $\beta := 2^{3\alpha+1} \binom{\min_{1 \leq j \leq n} \gamma_j}{2} = 2^{3\alpha+1} \gamma_n^{-2}$ .
    If  $d_n(F, L^2(\Omega)) \leq C_0 e^{-c_1 n^{\alpha}}$  for any  $n \in \{1, 2, \ldots\}$ , then  $\tau_n \leq C_0 \beta e^{-c_2 n^{-\alpha}}$  for  $n \geq 1$ , with  $\beta := 2 \binom{\min_{1 \leq j \leq n} \gamma_j}{2} = 2 \gamma_n^{-2}$ .

Lemmas 5 and 6 are the keys to derive the decay rates of the interpolation error of the GEIM Greedy algorithm. This is the purpose of the following theorem:

- 1) Assume that  $d_n(F, L^2(\Omega)) \leq C_0 n^{-\alpha}$  for Theorem 7: any  $n \geq 1$ , then the interpolation error of the GEIM Greedy selection process satisfies for any  $\varphi \in F$  the inequality  $\|\varphi - \mathcal{J}_n[\varphi]\|_{L^2(\Omega)} \le C_0(1 + \Lambda_n)\beta_n n^{-\alpha}$ , where the parameter  $\beta_n$  is defined as in lemma 5.
- 2) Assume that  $d_n(F, L^2(\Omega)) \le C_0 e^{-c_1 n^{\alpha}}$  for any  $n \ge 1$ , then the interpolation error of the GEIM Greedy selection process satisfies for any  $\varphi \in F$  the inequality  $\|\varphi - \mathcal{J}_n[\varphi]\|_{L^2(\Omega)} \le C_0(1+\Lambda_n)\beta_n e^{-c_2 n^{\alpha}}$ , where  $\beta_n$ and  $c_2$  are defined as in lemma 6.

*Proof:* It can be inferred from lemma 1 that,  $\forall \varphi \in$  $F, \|\varphi - \mathcal{J}_n[\varphi]\|_{L^2(\Omega)} \leq (1 + \Lambda_n) \|\varphi - P_n(\varphi)\|_{L^2(\Omega)} \leq$  $(1 + \Lambda_n)\tau_n$  according to the definition of  $\tau_n$ . We conclude the proof by bounding  $\tau_n$  thanks to lemmas 5 and 6.

Remark 3: If  $(\Lambda_n)_{n\geq 1}$  is a monotonically increasing sequence, then the sequence  $(\gamma_n)_{n\geq 1}$  in the GEIM procedure is monotonically decreasing. Using remark 2, the following decay rates in the generalized interpolation error can be derived:

- For any  $\varphi \in F$ , if  $d_n(F, L^2(\Omega)) \leq C_0 n^{-\alpha}$  for any  $n \ge 1$ , then the interpolation error of the GEIM Greedy selection process can be bounded as  $\|\varphi - \mathcal{J}_n[\varphi]\|_{L^2(\Omega)} \le$  $C_0 2^{3\alpha+1} (1+\Lambda_n)^3 n^{-\alpha}$ .
- For any  $\varphi \in F$ , if  $d_n(F, L^2(\Omega)) \leq C_0 e^{-c_1 n^{\alpha}}$  for any  $n \geq 1$ , then the interpolation error of the GEIM Greedy selection process can be bounded as  $\|\varphi - \mathcal{J}_n[\varphi]\|_{L^2(\Omega)} \le$  $C_0 2(1+\Lambda_n)^3 e^{-c_2 n^{\alpha}}$ .

Remark 4: The evolution of the Lebesgue constant  $\Lambda_N$  as a function of N is a subject of great interest. From the theoretical point of view, crude estimates exist and provide an exponential upper bound that is far from being what we get in the applications. As is shown in ([4], [5], [1]), the growth is lower than linear in N in the EIM situations. Our first experiments in the GEIM provide cases where it is uniformly bounded when evaluated in the  $\mathcal{L}(L^2)$  norm. We do not pretend that this is universal, but only shows that the theoretical exponentially increasing upper bound is far from being optimal in a class of sets F that have a small Kolmogorov n-width.

#### V. CONCLUSION

In this work, it has been proven that the approximation properties of the generalized interpolating spaces  $X_n$  lead to an error that has the same trend of the best possible choice and that is distant by a factor  $(1 + \Lambda_n)\beta_n$  from it. This has been proven in the case of a polynomial or exponential convergence in the n-width and is a first step towards the explanation of efficiency of this method in practice (as outlined in [7]).

#### **ACKNOWLEDGEMENTS**

This work was supported in part by the joint research program MANON between CEA-Saclay and University Pierre et Marie Curie-Paris 6.

#### REFERENCES

- [1] Y. Maday, N. Nguyen, A. Patera, and G. Pau, "A general multipurpose interpolation procedure: the magic points," Commun. Pure Appl. Anal., vol. 8(1), pp. 383-404, 2009.
- J. P. Kleijnen and W. C. van Beers, "Robustness of kriging when interpolating in random simulation with heterogeneous variances: Some experiments," European Journal of Operational Research, vol. 165, no. 3, pp. 826 – 834, 2005.
- H. Liu and S. Maghsoodloo, "Simulation optimization based on taylor kriging and evolutionary algorithm," Applied Soft Computing, vol. 11, no. 4, pp. 3451 – 3462, 2011.
- M. Barrault, Y. Maday, N. Y. Nguyen, and A. Patera, "An empirical interpolation method: Application to efficient reduced-basis discretization of partial differential equations." C. R. Acad. Sci. Paris, Série I., vol. 339, pp. 667-672, 2004.
- M. Grepl, Y. Maday, N. Nguyen, and A. Patera, "Efficient reduced-basis treatment of nonaffine and nonlinear partial differential equations." M2AN (Math. Model. Numer. Anal.), vol. 41(3), pp. 575-605, 2007.
- A. Kolmogoroff, "Über die beste Annäherung von Funktionen einer gegebenen Funktionenklasse," Annals of Mathematics, vol. 37, pp. 107-110, 1936.
- Y. Maday and O. Mula, "A generalized empirical interpolation method: application of reduced basis techniques to data assimilation," Analysis and Numerics of Partial Differential Equations, vol. XIII, pp. 221-236,
- [8] R. DeVore, G. Petrova, and P. Wojtaszczyk, "Greedy algorithms for reduced bases in banach spaces," Submitted.