

# On Quartic Transformational High Dimensional Model Representation

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**Abstract.** This work focuses on the development of a multivariate function approximating method by using quartic Transformational High Dimensional Model Representation (THDMR). The method uses the target function's image under a quartic transformation for High Dimensional Model Representation(HDMR) instead of the function's itself.

**Keywords:** Quartic Equation, Transformational High Dimensional Model Representation, Multivariate Functions

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## INTRODUCTION

Various HDMR versions were suggested in order to tackle with different problem types encountered. Factorized HDMR is one of them. The main problem with FHDMMR is that unlike additivity measures of HDMR, multiplicativity measures of FHDMMR is not well ordered. This led to the idea of logarithmic HDMR. The main idea behind Logarithmic HDMR was to initially transform what is basically a function of multiplicative nature to one that is of additive nature. This would enable us to expand the transformed problem using plain HDMR and then transform back the individual terms. Previous works were focused on the HDMR constancy optimization under an affine transformation[1, 2] and a conic transformation[3]. We shall consider in this work a quartic transformation and attempt to find optimal parameters for such a transformation leading to a new approximation.

## TRANSFORMATIONAL HIGH DIMENSIONAL MODEL REPRESENTATION

Let us consider a function  $f(x_1, \dots, x_N)$  of  $N$  independent variables  $x_1, x_2, \dots, x_N$  which has a non-additive structure. A transformation  $T$  can be chosen which yields a new multivariate function  $\varphi_j(x_1, \dots, x_N)$ .

$$Tf(x_1, \dots, x_N) = \varphi(x_1, \dots, x_N) \quad (1)$$

If we apply the HDMR expansion to  $\varphi$  we will get  $\varphi(x_1, \dots, x_N) = \varphi_0 + \sum_{\beta=1}^N \varphi_{\beta}(x_{\beta}) + \dots + \varphi_{1\dots N}(x_1, \dots, x_N)$ .

Additivity measurers  $\sigma_1(\varphi)$ s can be defined for this expansion in the usual HDMR manner.

$$\sigma_0(\varphi) = \frac{\|\varphi_0\|^2}{\|\varphi\|^2}, \quad \sigma_1(\varphi) = \sigma_0(\varphi) + \sum_{\beta_1=1}^N \frac{\|\varphi_{\beta_1}\|^2}{\|\varphi\|^2}, \quad \sigma_2(\varphi) = \sigma_1(\varphi) + \sum_{\substack{\beta_1, \beta_2=1 \\ \beta_1 < \beta_2}}^N \frac{\|\varphi_{\beta_1, \beta_2}\|^2}{\|\varphi\|^2}, \dots \quad (2)$$

These measures will be different from those obtained by applying HDMR expansion to the original function  $f$ . Obviously the difference will be dependent on the specific choice of the transformation  $T$ . Since the basic philosophy of HDMR is to be able to represent the function with as few and as less variate terms as possible, we would prefer  $\sigma_0$  and  $\sigma_1$  to be as close to 1 as possible. In this study we choose to deal only with  $\sigma_0$  and attempt to maximize it.

## QUARTIC TRANSFORMATIONAL HIGH DIMENSIONAL MODEL REPRESENTATION

A polynomial can be used as THDMR's operator for choosing the transformation suggested in (1). Here the degree of the polynomial will be taken to be four. The linear combination coefficients of the quartic will be assumed to vary with independent variables. They will be regarded as operators dependent on the algebraic operators each of which multiplies its operand with a different independent variable. This gives flexibility to the relevant transformation and they can be selected so as to approximate the HDMR expansion optimally. Since only  $\sigma_0(\varphi)$  will be under consideration,  $\varphi$  will be approximated by the constant component  $\varphi_0$

$$Tf(x_1, \dots, x_N) = \varphi(x_1, \dots, x_N) = a_0(x_1, \dots, x_N) + a_1(x_1, \dots, x_N)f + \dots + a_4(x_1, \dots, x_N)f^4 = \varphi_0$$

which gives the approximate equality

$$f_1 = \frac{a_3}{4a_4} - \frac{1}{2} \sqrt{\frac{\frac{a_3^2}{4a_4^2} - \frac{2a_2}{3a_4} + \frac{2^{\frac{1}{3}}p}{3a_4 \{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}}}{\frac{2^{\frac{1}{3}}p}{3a_4 \{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}} + \frac{\{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}}{2^{\frac{1}{3}}3a_4}}} - \frac{1}{2} \sqrt{\left( \frac{\frac{a_3^2}{2a_4^2} - \frac{4a_2}{3a_4} - \frac{2^{\frac{1}{3}}p}{3a_4 \{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}}}{\frac{2^{\frac{1}{3}}p}{3a_4 \{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}} - \frac{\{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}}{2^{\frac{1}{3}}3a_4}} \right) \left( -\frac{a_3^3}{a_4^3} + \frac{4a_3a_2}{a_4^2} - \frac{8a_1}{a_4} \right) / \left( 4 \sqrt{\frac{\frac{a_3^2}{4a_4^2} - \frac{2a_2}{3a_4} + \frac{2^{\frac{1}{3}}p}{3a_4 \{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}}}{\frac{2^{\frac{1}{3}}p}{3a_4 \{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}} + \frac{\{q + \sqrt{-4p^3 + q^2}\}^{\frac{1}{3}}}{2^{\frac{1}{3}}3a_4}}} \right)} \quad (3)$$

where

$$p = a_2^2 - 3a_3a_1 + 12a_4(a_0 - \varphi_0),$$

$$q = 2a_2^3 - 9a_3a_2a_1 + 27a_4a_1^2 + 27a_3^2(a_0 - \varphi_0) - 72a_4a_2(a_0 - \varphi_0).$$

In this work we will consider only  $f_1$ . The other roots may be considered analogically. The aim here is to find convenient forms for  $a_0, a_1, a_2, a_3$  and  $a_4$  that maximize  $\sigma_0$  in (3). To this end  $a_0, a_1, a_2, a_3$  and  $a_4$  will be taken in  $L^2$  class. Hence orthonormal basis of the Hilbert space  $H^{(N)}$  will be taken into consideration. Orthonormality will be defined  $(u_j, u_k) = \int_V dV W(x_1, \dots, x_N) u_j(x_1, \dots, x_N) u_k(x_1, \dots, x_N) = \delta_{jk}$ ,  $1 \leq j, k \leq \infty$ ; where  $V = [a_1, b_1] \times \dots \times [a_N, b_N]$  represents the hyperprism which is the HDMR construction domain and  $W(x_1, \dots, x_N)$  the multiplicative weight function used in HDMR. The individual weight functions will be chosen as constants, normalized over the corresponding domain and  $dV$  is the product of individual differentials  $dx_1 \dots dx_N$ .

Although the basis mentioned above has an infinite number of elements, in practice a finite number of elements will be taken into consideration. Therefore  $\varphi$  can be expressed as

$$\varphi(x_1, \dots, x_N) = \sum_{j=2}^m a_j^{(0)} u_j \left( \sum_{k=1}^n a_k^{(1)} u_k \right) f + \left( \sum_{l=1}^p a_l^{(2)} u_l \right) f^2 + \left( \sum_{s=1}^t a_s^{(3)} u_s \right) f^3 + \left( \sum_{v=1}^z a_v^{(4)} u_v \right) f^4 \quad (4)$$

To obtain the constant HDMR term  $\varphi_0$  both sides of (4) are to be integrated with respect to  $x_1, \dots, x_N$  over  $V$  under the weight function  $W$ . We define vectors  $\eta$  and  $\mu$ . The elements of vector  $\mu$  are defined as

$$\mu_j^{(0)} = \int_V dV \left( \prod_{\beta=1}^N W_{\beta}(x_{\beta}) \right) u_j = (u_j, h), \quad \mu_k^{(1)} = \int_V dV \left( \prod_{\beta=1}^N W_{\beta}(x_{\beta}) \right) u_j = (u_j, h) \dots \text{etc}$$

$h(x_1, \dots, x_N)$  appearing in the first inner product is a function which has the constant value 1 for all  $x_{\beta}$  in the first inner product is a function which has the constant value 1 for all  $x_{\beta}$  in the hyperprism domain  $[a_1, b_1] \times \dots \times [a_N, b_N]$ .  $\varphi_0$

can now be written as inner product  $\varphi_0 = \eta^T \mu$ . Since  $\varphi_0$  has a constant value, the square of its norm will be equal to the square of the function  $\varphi_0$ .  $\|\varphi_0\|^2 = |\eta \mu|^2 = \eta^T \mu \mu^T \eta$ .  $\|\varphi\|^2$  on the other hand can be expressed in terms of the above defined vector  $\eta$  and a square matrix  $\mathbf{A}$  which can be expressed in terms of its blocks as

$$\mathbf{A} \equiv \begin{bmatrix} \mathbf{K} & \mathbf{L} & \mathbf{N} & \mathbf{S} & \mathbf{B} \\ \mathbf{L}^T & \mathbf{M} & \mathbf{P} & \mathbf{T} & \mathbf{C} \\ \mathbf{N}^T & \mathbf{P}^T & \mathbf{R} & \mathbf{Y} & \mathbf{D} \\ \mathbf{S}^T & \mathbf{T}^T & \mathbf{Y}^T & \mathbf{Z} & \mathbf{F} \\ \mathbf{B}^T & \mathbf{C}^T & \mathbf{D}^T & \mathbf{F}^T & \mathbf{G} \end{bmatrix}$$

$$\begin{aligned} K_{jk} &\equiv (u_j, u_k), \quad 2 \leq j, k \leq m, \quad L_{jk} \equiv (u_j, f u_k), \quad 2 \leq j \leq m, \quad 1 \leq k \leq n, \quad M_{jk} \equiv (u_j, f^2 u_k), \quad 1 \leq j, k \leq n, \\ N_{jk} &\equiv (u_j, f^2 u_k), \quad 2 \leq j \leq m, \quad 1 \leq k \leq p, \quad P_{jk} \equiv (u_j, f^3 u_k), \quad 1 \leq j \leq n, \quad 1 \leq k \leq p, \\ R_{jk} &\equiv (u_j, f^4 u_k), \quad 1 \leq j, k \leq p, \quad S_{jk} \equiv (u_j, f^3 u_k), \quad 2 \leq j \leq m, \quad 1 \leq k \leq t, \\ T_{jk} &\equiv (u_j, f^4 u_k), \quad 1 \leq j \leq n, \quad 1 \leq k \leq t, \quad Y_{jk} \equiv (u_j, f^5 u_k), \quad 1 \leq j \leq p, \quad 1 \leq k \leq t, \quad Z_{jk} \equiv (u_j, f^6 u_k), \quad 1 \leq j, k \leq t, \\ B_{jk} &\equiv (u_j, f^4 u_k), \quad 2 \leq j \leq m, \quad 1 \leq k \leq z, \quad C_{jk} \equiv (u_j, f^5 u_k), \quad 1 \leq j \leq n, \quad 1 \leq k \leq z, \\ D_{jk} &\equiv (u_j, f^6 u_k), \quad 1 \leq j \leq p, \quad 1 \leq k \leq z, \quad F_{jk} \equiv (u_j, f^7 u_k), \quad 1 \leq j \leq t, \quad 1 \leq k \leq z, \quad G_{jk} \equiv (u_j, f^8 u_k), \quad 1 \leq j, k \leq z, \end{aligned}$$

$\mathbf{A}$  is a symmetric, positive definite matrix. Norm square of  $\varphi$  can be expressed in terms of  $\mathbf{A}$  and  $\eta$  as  $\|\varphi\|^2 = \eta^T \mathbf{A} \eta$ . So the constancy measurer  $\sigma_0$  becomes  $\sigma_0 = \eta^T \mu \mu^T \eta / \eta^T \mathbf{A} \eta$ . Our aim is to maximize  $\sigma_0$  which can be written as a Rayleigh quotient as  $(\mathbf{y}^T \mathbf{A}^{-1/2} \mu \mu^T \mathbf{A}^{-1/2} \mathbf{y}) / (\mathbf{y}^T \mathbf{y})$  where  $\mathbf{y} \equiv \mathbf{A}^{1/2} \eta$ . However, a Rayleigh quotient takes its maximum value at the maximum eigenvalue of its kernel, in this case  $\mathbf{A}^{-1/2} \mu \mu^T \mathbf{A}^{-1/2}$ . Similarly  $\mathbf{y}$  is the eigenvector corresponding to the maximum eigenvalue. An analysis of the kernel will give the maximum eigenvalue and the corresponding eigenvector of it. They are respectively,  $\sigma_0 = \mu^T \mathbf{A}^{-1} \mu$ ,  $\mathbf{y} = \mathbf{A}^{-1/2} \mu$ . The equation for  $\mathbf{y}$  gives us the vector  $\eta$  that maximizes  $\sigma_0$  as  $\eta = \mathbf{A}^{-1/2} \mathbf{y} = \mathbf{A}^{-1} \mu$ . Utilizing these equalities we can construct a function for  $\varphi_0$ . To complete this we can express  $\varphi_0, a_0, a_1, a_2, a_3$ , and  $a_4$  in terms of matrix algebraic entities.  $\varphi_0$  can be written in compact form as  $\varphi_0 = \eta^T \mu = \mu^T \mathbf{A}^{-1} \mu$ . We define a vector  $\xi$  with  $\xi = [\xi_2 \dots \xi_m \xi_1 \dots \xi_p \xi_1 \dots \xi_t \xi_1 \dots \xi_z]^T$  and express  $a_0, a_1, a_2, a_3$ , and  $a_4$  more compactly as  $a_0 = \eta^{(0)T} \xi^{(0)}$ ,  $a_1 = \eta^{(1)T} \xi^{(1)}$ ,  $a_2 = \eta^{(2)T} \xi^{(2)}$ ,  $a_3 = \eta^{(3)T} \xi^{(3)}$ ,  $a_4 = \eta^{(3)T} \xi^{(4)}$ .

Here the vectors  $\eta^{(0)}, \eta^{(1)}, \eta^{(2)}, \eta^{(3)}, \eta^{(4)}$  and  $\xi^{(0)}, \xi^{(1)}, \xi^{(2)}, \xi^{(3)}, \xi^{(4)}$  are explicitly defined as

$$\eta^{(0)} = [a_2^{(0)} \dots a_m^{(0)}]^T, \dots, \eta^{(4)} = [a_1^{(4)} \dots a_z^{(4)}]^T; \quad \xi^{(0)} = [\xi_2 \dots \xi_m]^T, \dots, \xi^{(4)} = [\xi_1 \dots \xi_z]^T;$$

To proceed we define  $(m+n+p+t+z-1) \times (m+n+p+t+z-1)$  projection matrices  $\mathbf{P}_1, \mathbf{P}_2, \mathbf{P}_3$  and  $\mathbf{P}_4$  as

$$\mathbf{P}_1 = \sum_{\beta=1}^{m-1} \mathbf{e}_\beta \mathbf{e}_\beta^T, \quad \mathbf{P}_2 = \sum_{\beta=1}^{m+n-1} \mathbf{e}_\beta \mathbf{e}_\beta^T, \quad \mathbf{P}_3 = \sum_{\beta=1}^{m+n+p-1} \mathbf{e}_\beta \mathbf{e}_\beta^T, \quad \mathbf{P}_4 = \sum_{\beta=1}^{m+n+p+t-1} \mathbf{e}_\beta \mathbf{e}_\beta^T.$$

Now these substitutions may be introduced into (3) to obtain

$$f_1 \approx -\frac{\sqrt{\chi}}{4} - \frac{1}{2} \sqrt{\frac{\chi}{4} - \gamma + \psi + \kappa} - \frac{1}{2} \sqrt{\frac{\chi}{2} - 2\gamma - \psi - \kappa + \frac{\chi^{3/2} - \frac{4a_2 \sqrt{\chi} - 8\mu^T \mathbf{A}^{-1} \mathbf{P}_2 \xi}{[\mu^T \mathbf{A}^{-1} (\mathbf{I} - \mathbf{P}_1 - \mathbf{P}_2 - \mathbf{P}_3 - \mathbf{P}_4) \xi]}}{4\sqrt{\frac{\chi}{4} - \gamma + \psi + \kappa}}}$$

where

$$\begin{aligned} p &= [\mu^T \mathbf{A}^{-1} \mathbf{P}_3 \xi]^2 - 3\mu^T \mathbf{A}^{-1} \mathbf{P}_4 \xi \mu^T \mathbf{A}^{-1} \mathbf{P}_2 \xi + 12\mu^T (\mathbf{I} - \mathbf{P}_1 - \mathbf{P}_2 - \mathbf{P}_3 - \mathbf{P}_4) \xi (\mu^T \mathbf{A}^{-1} \mathbf{P}_1 \xi - \mu^T \mathbf{A}^{-1} \mu), \\ q &= 2 [\mu^T \mathbf{A}^{-1} \mathbf{P}_3 \xi]^3 - 9\mu^T \mathbf{A}^{-1} \mathbf{P}_4 \xi \mu^T \mathbf{A}^{-1} \mathbf{P}_3 \xi \mu^T \mathbf{A}^{-1} \mathbf{P}_2 \xi + 27\mu^T (\mathbf{I} - \mathbf{P}_1 - \mathbf{P}_2 - \mathbf{P}_3 - \mathbf{P}_4) \xi [\mu^T \mathbf{A}^{-1} \mathbf{P}_2 \xi]^2 \end{aligned}$$

$$\begin{aligned}
& +27 [\mu^T \mathbf{A}^{-1} \mathbf{P}_4 \xi]^2 (\mu^T \mathbf{A}^{-1} \mathbf{P}_1 \xi - \mu^T \mathbf{A}^{-1} \mu) - 72 \mu^T (\mathbf{I} - \mathbf{P}_1 - \mathbf{P}_2 - \mathbf{P}_3 - \mathbf{P}_4) \xi \mu^T \mathbf{A}^{-1} \mathbf{P}_3 \xi \\
& \times (\mu^T \mathbf{A}^{-1} \mathbf{P}_1 \xi - \mu^T \mathbf{A}^{-1} \mu) \\
\chi = & \frac{[\mu^T \mathbf{A}^{-1} \mathbf{P}_3 \xi]^2}{[\mu^T (\mathbf{I} - \mathbf{P}_1 - \mathbf{P}_2 - \mathbf{P}_3 - \mathbf{P}_4) \xi]^2}, \quad \kappa = \frac{\{q + \sqrt{-4p^3 + q^2}\}^{1/3}}{2^{1/3} \mu^T (\mathbf{I} - \mathbf{P}_1 - \mathbf{P}_2 - \mathbf{P}_3 - \mathbf{P}_4) \xi} \\
\psi = & \frac{2^{1/3} p}{3 \mu^T (\mathbf{I} - \mathbf{P}_1 - \mathbf{P}_2 - \mathbf{P}_3 - \mathbf{P}_4) \xi \{q + \sqrt{-4p^3 + q^2}\}^{1/3}}, \quad \gamma = \frac{2 \mu^T \mathbf{A}^{-1} \mathbf{P}_3 \xi}{3 \mu^T (\mathbf{I} - \mathbf{P}_1 - \mathbf{P}_2 - \mathbf{P}_3 - \mathbf{P}_4) \xi}
\end{aligned}$$

To simplify expression we can use a spectral decomposition of  $\mathbf{A}^{-1}$ . A good approximation will be to use to minimal eigenpairs of  $\mathbf{A}$  as  $\mathbf{A}^{-1} = \lambda_{min}^{-1} \phi_{min} \phi_{min}^T$ .

## CONCLUSION

In this study we inserted certain flexibilities into the approximation. Because we want to improve its quality. Hence we applied HDMR on the image of the original function under a fourth degree transformation. The coefficients of the transformation are chosen to make the error of HDMR approximation as small as possible and this increases the efficiency of the method.

## REFERENCES

1. İ. Yaman, "Construction of New Rational Approximation Based on Transformational High Dimensional Model Representation and Efficient Usage of Them by Fluctuation Approximation", Ph.D Thesis, İstanbul Technical University Informatics Institute, December 2008.
2. İ. Yaman, M. Demiralp, A New Rational Approximation Technique Based on Transformational High Dimensional Model Representation, Springer U.S.line Volume 52, NO. 3/November, 2009, pp.385-407, ISSN: 1017-1398 (Print).
3. Z. Gündoğar, N.A. Baykara, M. Demiralp, Basic Features of Conic Transformational High Dimensional Model Representation, Int. Conf. on Numerical Analysis and Applied Mathematics, Rhodes, Greece, 2010.
4. M. Demiralp, Transformational High Dimensional Model Representation, International Conference of Computational Methods in Engineering, Crete, Greece, 2006.