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**Notes** 

## **Elimination of linear parameters in non-linear regressions: a fast and effective method for the determination of binding parameters**

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## **Abstract**

A semi-linear least-squares regression methodology is proposed to extract binding parameters from experimental binding data. After legitimation of simplification and suitable mathematical transformation, the only non-linear parameter which remains to be searched for by a non-linear least-squares regression is the affinity constant. As a result, number of sites and affinity constants are easier to grasp than with a full non-linear regression. This methodology can be applied to saturation as well as to displacement binding studies. It has been tested with binding data of QNB and  $\alpha$ BTX on rat hippocampus synaptosomes.

*Keywords:* Binding parameters; Nonlinear regression; Semilinear regression; Least-squares fitting procedure; Cholinergic receptor

The determination of 'binding parameters' (affinity constants, binding capacities and non specific binding) by a non-linear least-squares fitting procedure may be time-consuming. Firstly, it requires the identification of the model (one, two... or more classes of sites). Secondly, for each of these models, the speed of convergence towards the minimum minimorum of the cost function is iterative, and therefore, frequently slow, especially when many parameters are effective. The following method is considerably faster than those commonly used for the determination of binding parameters. It is based on the reduction of the number of non-linear parameters.

For saturation studies, the equations currently used to calculate the whole binding level of the ligand i  $(B_i)$ : specific + non-specific levels) is, according to the terminology of Feldman (1972), Munson and Rodbard (1979, 1980) and Munson (1983):

$$
(B_i^{\text{calc}}) = \sum_i \frac{K_{ij} R_j (L_i - B_i^{\text{calc}})}{1 + K_{ij} (L_i - B_i^{\text{calc}})} + N_i (L_i - B_i^{\text{calc}})
$$
\n(1)

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Table 1<br>Results from saturation curve of a radiolabelled ligand: comparison with the fully non-linear process results



Table 2

P. Cognez et al. / International Journal of Pharmaceutics 123 (1995) 137-142

where  $K_{ij}$  is the affinity constant of the class of sites  $j$ ,  $L_i$  denotes the total concentration of the ligand i,  $R_i$  is the binding capacity of the class of sites j, and  $N_i$  represents the non-specific binding constant.

This identification of the model implies performing the computation of *(B i)* successively with  $j = 1, 2...$  Moreover, this computation implies solving a  $j + 1$  degree equation in  $(B<sub>i</sub>)$  to perform a strictly pure simulation (i.e., without mixing experimental and calculated  $(B_i)$  values: the best way to avoid, as much as possible, the propagation of errors (Sands, 1974)).

It is noteworthy that in Eq. 1, the parameters we are looking for,  $K_{ii}$ ,  $R_i$  and  $N_i$  can be gathered in the linear terms  $(K_{ij}R_j)$ and  $N_i$  and in the non-linear one  $K_{ij}$ , provided that, in the right member of Eq. 1 ( $B_i^{\text{calc}}$ ) are replaced by the known experimental values  $(B_i^{exp})$ . This reduced classification is frequently adopted for the treatment of mathematical models in physics and has been studied elsewhere (Lawton and Sylvestre, 1971; Barham and Drane, 1972; Harville, 1973); it should be noted that this methodology has never been applied in the field of binding studies. As a result, the model (Eq. 1) becomes a non-linear one only in the parameter(s)  $K_{ij}$ . An initial guess of the  $K_{ii}$  values allows us, with total certainty, to obtain immediately the parameters  $(K_{ij}R_j)$ and  $N_i$  by a strictly linear least-squares proce-

Table 3

Results from the displacement of variable labelled ligand concentrations  $(L_i)$  by a fixed concentration (*l*) of the same unlabelled one: comparison with the fully non-linear process results

<b>ONB</b>			$\alpha$ BTX		
$(L, \text{ from } 1 \times 10^{-11} \text{ to } 1 \times 10^{-8} \text{ M}: l = 1 \times 10^{-9} \text{ M})$			$(L_i \text{ from } 1 \times 10^{-11} \text{ to } 5 \times 10^{-8} \text{ M: } l = 5 \times 10^{-10} \text{ M})$		
12.735		Theoretical minimum $U$ Semi-linear regression	26.032 $U$ minimum minimorum		
$U$ minimum minimorum					
Two specific receptors One specific receptor 258.994 34.541 Values of the parameters obtained			One specific receptor 94.879		Two specific receptors 9108.004
Ligand $a$ Semi-linear $1.228 \times 10^{9}$ $1.086 \times 10^{-9}$ $4.866 \times 10^{-2}$	Our programme $1.183 \times 10^{9}$ $1.117 \times 10^{-9}$ $4.777 \times 10^{-2}$		Semi-linear $7.871\times10^{8}$ $3.138 \times 10^{-11}$ $1.396 \times 10^{-3}$	Ligand <sup>a</sup>	Our programme $8.085 \times 10^{8}$ $3.113 \times 10^{-11}$ $1.399 \times 10^{-3}$
Theoretical minimum $U$ 14.96 Semi-linear regression $U$ minimum minimorum					
One specific receptor 32.18	Two specific receptors 635.588				
(1st model, 2nd model excluded)					
Semi-linear Ligand <sup>a</sup> $1.284 \times 10^{9}$ $1.26 \times 10^{-9}$ $4.903\times10^{-2}$	Our programme $1.125 \times 10^{9}$ $1.389 \times 10^{-9}$ $3.423 \times 10^{-2}$				
		(1st model, 2nd model excluded) $(L_i$ from $1 \times 10^{-11}$ to $1 \times 10^{-8}$ M: $l = 1 \times 10^{-8}$ M) Values of the parameters obtained			Values of the parameters obtained (1st model, 2nd model excluded)

<sup>a</sup> Ligand is not programmed for such calculations.

dure. Indeed, deriving simultaneously the  $U$  cost function vs the  $(K_{ii}R_i)$  and  $N_i$  parameters:

$$
\frac{\delta U}{\delta (K_{ij}R_j)} = 0 \quad \frac{\delta U}{\delta N_i} = 0
$$

leads to the classical set of linear equations in  $(K_{ii}R_i)$  and  $N_i$  parameters which are easily solved. Using the optimal parameters resulting from this derivation in the expression of  $U$  gives, in fact, a value which depends only on the  $K_{ii}$ parameter(s). The process is repeated with only different  $K_{ii}$  term(s) until the minimum minimorum is obtained. This can be achieved by the usual ways of minimization of the objective function (Walsh, 1979).

This 'semi-linear' method has been applied to original binding results of quinuclidinyl 4- *[phenyl-3H]benzilate* (47 Ci/mmol; QNB) and *N-[ propionyl-*<sup>3</sup>H]propionylated  $\alpha$ -bungarotoxin (54 Ci/mmol;  $\alpha$ BTX) with cholinergic receptors from synaptosomes of rat hippocampus homogenized according to classical methodologies (Whittaker and Barker, 1972; Yamamura and Snyder, 1974; Marks and Collins, 1982; Schwartz et al., 1982; Gurwitz et al., 1984; Hulme and Birdsall, 1992).

This methodology can be extended to experiments of the displacement of a radiolabelled ligand by the same unlabelled one. This can readily be achieved by an original modification of Eq. 1 using an experimentally known  $\alpha$  term:

$$
(B_i^{\text{calc}}) = \sum_i \frac{K_{ij}R_j(L - B_i^{\text{calc}})}{1 + \alpha_i K_{ij}(L - B_i^{\text{calc}})}
$$

$$
+ N_i(L - B_i^{\text{calc}})
$$
(2)

or

$$
(B_i^{\text{calc}}) = \sum_i \frac{K_{ij} R_j (L_i - B_i^{\text{calc}})}{1 + \alpha_i K_{ij} (L_i - B_i^{\text{calc}})}
$$

$$
+ N_i (L_i - B_i^{\text{calc}})
$$
(3)

where  $L$  is the fixed and  $L_i$  the variable concentration(s), in each  $i$  point, of the labelled ligand, according to the type of experiments.

In Eq. 2  
\n
$$
\alpha_i = \frac{L + l_i}{L}
$$
\nand in Eq. 3  
\n
$$
l + L_i
$$

 $a_i$   $l$  $L$  representing the radiolabelled ligand and  $l$ 

corresponding to the same unlabelled ligand. The introduction of the  $\alpha_i$  parameters is very efficient, since Eq. 2 and 3 exhibit a very close analogy with Eq. 1 and so can be handled with the described semi-linear methodology by grouping  $\alpha_i$  with the  $(L_i - B_i^{\text{calc}})$  or  $(L - B_i^{\text{calc}})$  terms.

It is noteworthy that the values resulting from the semi-linear regression are very close to those obtained by the true non-linear methodology and can, of course, be used as starting values for the fully non-linear regression.

It appears that with the proposed methodology the binding parameters as well as the number of receptors can be obtained faster than by using the usual strictly non-linear methodology.

This procedure may be very useful to any authors studying the field of binding.

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