

Linear-quadratic rational polynomial families versus Hill in an analysis of human thymidine kinase 1 data

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Abstract

Background

The Hill reaction rate model is useful because it is flexible enough to represent many reactions and because it characterizes the extent to which biochemical reactions exhibit cooperativity. Its main disadvantage is that it cannot discriminate between cooperativity mediated by changes in enzyme activity versus substrate binding affinity.

Results

The linear-quadratic rational polynomial (LQRP) reaction rate models explored here assume:

(1) that binding of enzyme monomers to form dimers is well approximated as being infinitely tight at the enzyme concentrations of the data, (2) that the behavior of any higher order enzyme structures (if they exist) is dominated by the behavior of dimers within such structures, and (3) that the enzyme concentrations are so low relative to the lowest substrate concentration that free substrate concentrations approximately equal total substrate concentrations. In addition to these assumptions, hypotheses of dissociation constants K being equal to each other or infinitely large, and hypotheses of enzyme activities k being equal to each other or zero, yields a family of k - K LQRP models. These k - K LQRPs map, typically many-to-one, into data fitting equivalent canonical LQRPs. The canonical LQRPs were fitted to human thymidine kinase 1 data. Predictions of the top models (ranked by the Akaike Information Criterion) suggest subsequent experiments to distinguish TK1 cooperativity mechanisms mediated primarily by changes in k , K or both k and K .

Conclusions

Compared to single model fits of the empirical Hill model, fits of families of rational polynomials, such as those presented here, are preferable because they yield predictions that can guide subsequent experiments to elucidate mechanisms.

Background

The empirical Hill model of reaction fluxes v as a function of substrate concentrations S is

$$v = \frac{V_{\max} \left(\frac{S}{S_{50}} \right)^n}{1 + \left(\frac{S}{S_{50}} \right)^n} \quad (1)$$

where V_{\max} is the maximum flux, S_{50} is the substrate concentration at which the flux is half maximum, and n is greater than 1 for positive cooperativity and less than 1 for negative cooperativity. This model is useful because it is flexible enough to represent many reactions, and because it characterizes the extent to which biochemical reactions exhibit cooperativity. Its disadvantage is that it cannot discriminate between cooperativity mediated by changes in enzyme activity versus cooperativity mediated by changes in substrate binding affinity.

The linear-quadratic rational polynomial (LQRP) models explored here assume: (1) that binding of enzyme monomers to form enzyme dimers is approximately infinitely tight across the enzyme concentrations of interest, (2) that the behavior of any higher order enzyme structures (if they exist) is dominated by the behavior of dimers within such structures, and (3) that enzyme concentrations are so low relative to the lowest substrate concentration that free substrate concentrations approximately equal total substrate concentrations. Added to these assumptions are hypotheses of various dissociation constants K being equal to each other or being infinitely large, and hypotheses of enzyme complex activities k being equal to each other or being well approximated as zero. These hypotheses generate a family of k - K LQRP models/hypotheses (see Table 1) which map, typically many-to-one, into data fitting equivalent canonical V - α LQRPs (e.g. Eqs. 3-9 below). This paper explores the fitting of V - α LQRP models first to simulated Hill data with Hill coefficients of .4, .7, 1.3, and 1.6, and then to published human thymidine kinase 1 data [1-5].

Results

The LQRP model family

LQRP hypotheses/models were created as parameter constraints applied to the model

$$v = \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S}{K_1} + \frac{S}{K_2} + \frac{S^2}{K_1 K_3}} [E_0] \quad (2)$$

where k_i and K_i are the activity and dissociation constants of the i th potentially active enzyme complex in Figure 1 and $[E_0]$ is the total concentration of enzyme *dimers*. Because Eq. (2) has six parameters where at most four can be identified (see Eq. 3 below), it follows that at least two parameters must be eliminated from Eq. (2) by parameter constraints before fitting the resulting model to a dataset. This leads to many models. Indeed, 37 k - K LQRPs (Table 1) arise from Eq. (2) without the use of $k_i = 0$ constraints (these will be dealt with later). These k - K LQRPs can be grouped into 7 data fitting equivalence classes that can be represented by the following 7 canonical V - α LQRPs:

4-parameter model
$$v = \frac{V_1 S + V_\infty \alpha_2 S^2}{1 + 2\alpha_1 S + \alpha_2 S^2} \quad (3)$$

3-parameter models
$$v = \frac{V_\infty (\alpha_1 S + \alpha_2 S^2)}{1 + 2\alpha_1 S + \alpha_2 S^2} \quad (4)$$

$$v = \frac{V_1 S + V_\infty \alpha_1^2 S^2}{(1 + \alpha_1 S)^2} \quad (5)$$

$$v = \frac{V_1 S + V_\infty \alpha_1^2 S^2}{1 + \alpha_1 S + \alpha_1^2 S^2} \quad (6)$$

2-parameter models
$$v = \frac{V_\infty (.5\alpha_1 S + \alpha_1^2 S^2)}{1 + \alpha_1 S + \alpha_1^2 S^2} \quad (7)$$

$$v = \frac{V_\infty \alpha_1 S}{1 + \alpha_1 S} \quad (8)$$

$$v = \frac{V_{\infty}\alpha_1 S^2}{1 + \alpha_1 S^2} \quad (9)$$

where V_{∞} is the flux in the limit of large S . Examples of derivations of these equations follow:

$K_1 = K_2 \neq K_3$ and $k_1 = k_2 \neq k_3$ (row 1 in Table 1) yields Eq. (3)

$$v = \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S}{K_1} + \frac{S}{K_2} + \frac{S^2}{K_1 K_3}} [E_0] = \frac{2k_1 \frac{S}{K_1} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + 2\frac{S}{K_1} + \frac{S^2}{K_1 K_3}} [E_0] \quad (10)$$

if $V_1 = 2k_1[E_0]/K_1$, $V_{\infty} = 2k_3[E_0]$, $\alpha_1 = 1/K_1$, and $\alpha_2 = 1/(K_1 K_3)$. Rows in Table 1 that map to Eq. (3) represent mechanisms in which cooperativity is mediated by changes in both k and K , save two (rows 11 and 12) that assume equalities across the k if the condition $2k_3 = k_1 + k_2$ is classified as such (and it is here). One of these two rows is the case of a rigid asymmetric dimer defined by $K_1 \neq K_2 = K_3$ and $2k_3 = k_1 + k_2$ (row 12). This case reduces to a model of a mixture of two independent monomer enzymes that use the same substrate as follows

$$\begin{aligned} v &= \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S}{K_1} + \frac{S}{K_2} + \frac{S^2}{K_1 K_3}} [E_0] = \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + (k_1 + k_2) \frac{S^2}{K_1 K_2}}{\left(1 + \frac{S}{K_1}\right) \left(1 + \frac{S}{K_2}\right)} [E_0] \\ &= \frac{k_1 \frac{S}{K_1} \left(1 + \frac{S}{K_2}\right) + k_2 \frac{S}{K_2} \left(1 + \frac{S}{K_1}\right)}{\left(1 + \frac{S}{K_1}\right) \left(1 + \frac{S}{K_2}\right)} [E_0] = \left(\frac{k_1 \frac{S}{K_1}}{\left(1 + \frac{S}{K_1}\right)} + \frac{k_2 \frac{S}{K_2}}{\left(1 + \frac{S}{K_2}\right)} \right) [E_0] = \frac{V_{m1} \frac{S}{K_1}}{\left(1 + \frac{S}{K_1}\right)} + \frac{V_{m2} \frac{S}{K_2}}{\left(1 + \frac{S}{K_2}\right)} \quad (11). \end{aligned}$$

Since substrate will always bind the site with the tighter of K_1 and K_2 first, positive cooperativity cannot be represented by this model, though negative cooperativity can.

Rewriting Eq. (11) as

$$v = \frac{\left(\frac{k_1}{K_1} + \frac{k_2}{K_2}\right)S + (k_1 + k_2) \frac{S^2}{K_1 K_2}}{1 + \left(\frac{1}{K_1} + \frac{1}{K_2}\right)S + \frac{S^2}{K_1 K_2}} [E_0] = \frac{V_1 S + V_{\infty} \alpha_2 S^2}{1 + 2\alpha_1 S + \alpha_2 S^2} \quad (11b)$$

shows that, although α_1 and α_2 are free to be any real coefficients in Eq. (3), they are restricted in (11b) to yield real roots. Further, α_1 cannot increase or decrease without increasing or decreasing α_2 , and *vice-versa*, and if $k_1 + k_2$ increases or decreases to increase or decrease V_∞ , so too must $V_1 = \frac{k_1}{K_1} + \frac{k_2}{K_2}$ also increase or decrease, and *vice-versa*. Thus, when forced into the structure of Eq. (3), we see that Eq. (11) is a subset of Eq. (3), though both are four parameter models. Since Eq. (3) can fit any dataset as well as Eq. (11), but it can also fit positive cooperativity data which Eq. (11) cannot, it follows that Eq. (3) will always tie (if $n < 1$) or do better than (if $n > 1$) Eq. (11), i.e. Eq. (11) does not create an additional V - α model since v - S data cannot discriminate it from Eq. (3) k - K models/hypotheses.

$K_1 = K_2 \neq K_3$ and $k_1 + k_2 = 2k_3$ (row 10) yields Eq. (4)

$$v = \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S}{K_1} + \frac{S}{K_2} + \frac{S^2}{K_1 K_3}} [E_0] = \frac{2k_3 \left(\frac{S}{K_1} + \frac{S^2}{K_1 K_3} \right)}{1 + 2 \frac{S}{K_1} + \frac{S^2}{K_1 K_3}} [E_0] = \frac{V_\infty (\alpha_1 S + \alpha_2 S^2)}{1 + 2\alpha_1 S + \alpha_2 S^2} \quad (12).$$

Further, all of the other Eq. (4) rows in Table 1 are also consistent with cooperativity being mediated by inequalities in K 's rather than k 's.

$K_1 = K_2 = K_3$ in rows 17 to 20 yield Eq. (5)

$$v = \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S}{K_1} + \frac{S}{K_2} + \frac{S^2}{K_1 K_3}} [E_0] = \frac{(k_1 + k_2) \frac{2S}{K_1} + 2k_3 \frac{S^2}{K_1^2}}{1 + 2 \frac{S}{K_1} + \frac{S^2}{K_1^2}} [E_0] = \frac{V_1 S + V_\infty \alpha_1^2 S^2}{1 + 2\alpha_1 S + \alpha_1^2 S^2} = \frac{V_1 S + V_\infty \alpha_1^2 S^2}{(1 + \alpha_1 S)^2} \quad (13).$$

These are k cooperativity mechanisms.

$K_1 = K_3$ and $K_2 = \infty$ and $k_1 \neq k_3$ (row 28) maps to Eq. (6)

$$v = \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S}{K_1} + \frac{S}{K_2} + \frac{S^2}{K_1 K_3}} [E_0] = \frac{k_1 \frac{S}{K_1} + 2k_3 \frac{S^2}{K_1^2}}{1 + \frac{S}{K_1} + \frac{S^2}{K_1^2}} [E_0] = \frac{V_1 S + V_\infty \alpha_1^2 S^2}{1 + \alpha_1 S + \alpha_1^2 S^2} \quad (14)$$

and is an example of a mixed k - K cooperativity mechanism.

$K_1 = K_3$ and $K_2 = \infty$ and $k_1 = k_3$ (row 29), a K cooperativity mechanism, maps to Eq. (7) as

$$v = \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S}{K_1} + \frac{S}{K_2} + \frac{S^2}{K_1 K_3}} [E_0] = \frac{2k_3 \left(.5 \frac{S}{K_1} + \frac{S^2}{K_1^2} \right)}{1 + \frac{S}{K_1} + \frac{S^2}{K_1^2}} [E_0] = \frac{V_\infty (.5 \alpha_1 S + \alpha_1^2 S^2)}{1 + \alpha_1 S + \alpha_1^2 S^2} \quad (15).$$

$k_1 = k_2 = k_3$ and $K_1 = K_2 = K_3$ (row 21) yields Eq. (8)

$$v = \frac{k_3 \left(2 \frac{S}{K_1} + 2 \frac{S^2}{K_1^2} \right)}{1 + 2 \frac{S}{K_1} + \frac{S^2}{K_1^2}} [E_0] = \frac{k_3 2 \frac{S}{K_1} \left(1 + \frac{S}{K_1} \right)}{\left(1 + \frac{S}{K_1} \right) \left(1 + \frac{S}{K_1} \right)} [E_0] = \frac{k_3 2 \frac{S}{K_1}}{\left(1 + \frac{S}{K_1} \right)} [E_0] = \frac{V_\infty \alpha_1 S}{1 + \alpha_1 S} \quad (16)$$

or the Hill model in Eq. (1) with $n = 1$, i.e. the Michaelis-Menten model. The Eq. (8) rows of 30, 31 and 32 in Table 1 prove that inequalities in K 's and k 's do not imply cooperativity.

$K_1 = \infty$, $K_2 = \infty$ and $K_1 K_3$ finite (row 34) yields Eq. (9)

$$v = \frac{k_1 \frac{S}{K_1} + k_2 \frac{S}{K_2} + 2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S}{K_1} + \frac{S}{K_2} + \frac{S^2}{K_1 K_3}} [E_0] = \frac{2k_3 \frac{S^2}{K_1 K_3}}{1 + \frac{S^2}{K_1 K_3}} [E_0] = \frac{V_\infty \alpha_2 S^2}{1 + \alpha_2 S^2} \quad (17)$$

or the Hill model in Eq. (1) with $n = 2$, $S_{50} = 1/\sqrt{\alpha_2} = \sqrt{K_1 K_3}$, and $V_{\max} = V_\infty = 2k_3 [E_0]$. This model hypothesizes that although K_1 and K_2 are so large that single substrate enzyme dimers cannot be detected above noise, K_3 is tight enough that $K_1 K_3$ products must be treated as

being finite, i.e. it hypothesizes that the presence of substrate saturated dimers can be detected. This equation represents a K cooperativity mechanism because the values of k_1 and k_2 can be anything and can thus be thought of as being equal to k_3 .

Other V - α LQRPs arise when $k_i = 0$ hypotheses are applied to Table 1 rows as follows:

Eq. (3) derivatives

$k_3 = 0$ applied to any of the Eq. (3) rows of Table 1 yields

$$v = \frac{V_1 S}{1 + 2\alpha_1 S + \alpha_2 S^2} \quad (18)$$

which, along with Eqs. (24) and (27), is distinguished by its drops back to zero at large S .

$k_3 \neq 0$, $k_1 = 0$ and $k_2 = 0$ applied to the Eq. (3) rows in Table 1 in which neither k_1 nor k_2 are constrained to equal k_3 yields

$$v = \frac{V_\infty \alpha_2 S^2}{1 + 2\alpha_1 S + \alpha_2 S^2} \quad (19), \text{ and}$$

$k_3 \neq 0$ and $k_1 = 0$ or $k_2 = 0$ in Eq. (3) rows where one of k_1 and k_2 is constrained to equal k_3 yields, via rows 2 and 3,

$$v = \frac{V_\infty (.5\alpha_1 S + \alpha_2 S^2)}{1 + 2\alpha_1 S + \alpha_2 S^2} \quad (20),$$

via row 5,

$$v = \frac{V_\infty (.5\sqrt{\alpha_2} S + \alpha_2 S^2)}{1 + 2\alpha_1 S + \alpha_2 S^2} \quad (21),$$

via row 6,

$$v = \frac{V_\infty (.5\alpha_1 S + \alpha_2 S^2)}{1 + (\alpha_1 + \sqrt{\alpha_2})S + \alpha_2 S^2} \quad (22),$$

and via rows 8 and 9,

$$v = \frac{V_{\infty} (.5\alpha_1 S + \alpha_1 \alpha_2 S^2)}{1 + (\alpha_1 + \alpha_2)S + \alpha_1 \alpha_2 S^2} \quad (23).$$

Eq. (4) derivatives

In each of the Eq. (4) models in Table 1, k_1 and k_2 are constrained to either equal k_3 or sum to $2k_3$, and since $k_3 \neq 0$, else the rate law trivially vanishes, no new LQRP's are formed.

Eq. (5) derivatives

If $k_3 = 0$ these rows yield

$$v = \frac{V_1 S}{(1 + \alpha_1 S)^2} \quad (24),$$

else, row 18 yields

$$v = \frac{V_{\infty} \alpha_1^2 S^2}{(1 + \alpha_1 S)^2} \quad (25),$$

rows 19 and 20 yield

$$v = \frac{.5V_{\infty} \alpha_1 S + V_{\infty} \alpha_1^2 S^2}{(1 + \alpha_1 S)^2} \quad (26),$$

and row 17 reproduces Eq. (5).

Eq. (6) derivatives

With $k_3 = 0$ row 28 creates

$$v = \frac{V_1 S}{1 + \alpha_1 S + \alpha_1^2 S^2} \quad (27)$$

and with $k_1 = 0$ it creates

$$v = \frac{V_{\infty} \alpha_1^2 S^2}{1 + \alpha_1 S + \alpha_1^2 S^2} \quad (28).$$

Eq. (7), Eq. (8) and Eq. (9) derivatives

When $k=0$ hypotheses are applied to these Table 1 rows the models either collapse to $v=0$ or remain unchanged by either a factor of 1 or 2 being absorbed into V_∞ . Thus, no additional V - α LQRP models are formed.

LQRP versus Hill model with $n = .4, .7, 1.3$ and 1.6

Hill models with $V_{\max} = 1$, $S_{50} = 1 \mu\text{M}$, and $n = (.4, .7, 1.3, \text{ and } 1.6)$ were simulated with 1% added noise at 100 logarithmically spaced S values between .1 and 10 μM . The resulting “data” was then fitted to Eqs (3-9) and Eqs (18-28) to yield the plots in Figure 2 and the parameter estimates in Table 2 (reproducible by the R [6] script in Additional File 1). Using the Akaike Information Criterion (AIC) [7] and a ΔAIC_c (see Methods) cut-off of 15 for model rejection [8] (models not rejected have asterisks in the legend in Fig. 2), Eqs. (3) and (4) fit the hill data well at all four n values, and Hill coefficients closer to 1 (.7 and 1.3) were fitted well by more LQRPs than Hill coefficients further from 1 (.4 and 1.6).

LQRP fits to the Birringer et al human thymidine kinase 1 data

The complete set of V - α LQRP models was fitted to recent human thymidine kinase 1 data of Birringer et al. [1] (Table 8 and Additional File 2). The fits are shown in Fig. 3 (which can be regenerated by Additional File 3). With models ranked by AIC_c , Table 3 shows that the Hill model was far from being selected as the best model. The top model, Eq. (25), is consistent with $k_1 = k_2 = 0$ and $K_1 = K_2 = K_3$ (Table 1, row 18), i.e. an extreme case of positive cooperativity mediated by changes in k (since $k_3 > 0$) rather than changes in K . This k - K LQRP is

$$v = \frac{2k_3 \frac{S^2}{K_1^2}}{1 + 2\frac{S}{K_1} + \frac{S^2}{K_1^2}} 30 \times 153 \times 10^{-6} \quad (29)$$

where $[E_0]=153$ pM [1] (306 pM was the monomer concentration) and the reaction vessel volume was 30 μ L [1]. Upon fitting Eq. (29) to this data the parameter estimates, upon conversion to seconds, were $k_3 = 0.2746$ (0.2545333, 0.2962) sec^{-1} and $K_1 = 0.266$ (0.207, 0.337) μ M (95% confidence intervals are shown in parentheses, see Additional File 4). Meanwhile, the Hill parameter estimates of the original data analysis were $k_{\text{cat}}=.28/\text{sec}$, $n=1.3$, and $S_{50}=.51$ μ M [1]. These activities are low relative to maximum velocities on the order of 10 μ mole/min/mg found by Munch-Peterson's group [2, 3, 5] and others [4]. Since 10 μ moles per minute is 167 nmoles/sec, and since 1 mg of protein is $1\text{mg}/(25 \times 10^6 \text{ mg/mole}) = 40$ nmoles, 10 μ moles/min/mg is roughly 4 turnovers per second, i.e. the activity in Birringer et al. is roughly 16-fold lower than expected based on earlier studies.

The second best fitting model (Eq. 28) proposes k_1 is zero and that the value of k_2 does not matter since $K_2 = \infty$. Thus, this model is consistent with cooperativity being mediated by both activity changes and affinity changes. The third best model (Eq. 7) proposes that k_1 is the same as k_3 and that k_2 does not matter since $K_2 = \infty$, i.e. it proposes affinity changes as the mechanism. Finally, the fourth best model is Eq. (26) which derives from rows 19 and 20 in Table 1 which claim that k_1 or k_2 is zero while k_3 is not, and that the K are all the same, i.e. it too supports changes in k as the mechanism of cooperativity. Thus, the top 4 models place 2.5 votes in favor of activity changes and 1.5 votes in favor of binding affinity changes. The 5th best model, the Michaelis-Menten model (Eq. 8), is disfavored by $\Delta\text{AIC}_c > 3.5$. Of the ΔAIC_c gap of ~ 4 that follows this two parameter model, ~ 2 is due to the small sample correction term (see Methods) and 2 is due to an additional parameter (the 6th to 10th models

are all three parameter models). This suggests that if three parameter models are to compete, additional data is needed to increase the sum of squared errors component of the AIC_c and thus decrease the relative importance of parameter numbers.

LQRP fits to other human thymidine kinase 1 data

Tables 4 to 7 show the results of fitting the LQRPs to other data [2-5]. Strikingly, the top 4 models of the dataset of Frederiksen et al.[2] (Table 4) are the same as those for Birringer et al. [1]. One of these top 4 models (Eq. 7) is also the best model of the Berenstein et al. [3] data (Table 5). The data of Li et al. [4] is different in that the Michaelis-Menten model wins (the Hill coefficient was 1.01, see Table 6), and the data of Munch-Petersen et al. [5] is different in that the 4 parameter model of Eq. (3) (see Table 7) is its clear winner.

Joint LQRP fits to human thymidine kinase 1 data

Datasets with Hill coefficients of 1.2 to 1.3 [1-3, 5] (i.e. excluding the non-cooperative data of Li et al.) were amplitude normalized by dividing their fluxes v by V_{max} of their Hill model fits (see Additional File 5). These datasets were then fitted jointly to Eqs (3)-(9) and Eqs (18)-(28). Eq. (7) won this competition, and oddly, the Hill model came in second place with a ΔAIC_c of ~ 2 (not shown). If the Hill model approximates an average of more than one LQRP, this result could indicate that the datasets are too different to merge. The 1993 dataset [5] was thus removed. The result was approximately the same, i.e. Eq. (7) won and the Hill model came in second. The 2000 dataset [3] was then also removed, leaving just the merged normalized data of Birringer et al. [1] and Frederiksen et al. [2]. The Hill model then fell out of the competition and Eq. (25) came in first place and Eq. (7) in second (with a ΔAIC_c of ~ 2.5). These top two models differ in their predictions the most at thymidine concentrations greater than $100 \mu M$ and between $.2$ and $.5 \mu M$ (see Fig. 4 and Additional File 6).

Subsequent experiments should thus be performed at these concentrations.

Discussion

Since there are 7 Eq. (8) rows in Table 1, the Michaelis-Menten model does not suggest a mechanism. Similarly, Eq. (3) appears in 12 rows in Table 1, so its victory in fitting the data of Munch-Petersen et al. [5] also leaves the underlying k - K model/mechanism undefined. In contrast, Eq. (7) appears in Table 1 only once, and Eq. (25) is strictly a derivative of row 18, so when one of these V - α LQRP models is the best, a specific k - K hypothesis is supported.

It should be clear that LQRPs cannot represent datasets with Hill coefficients greater than 2 and that, to handle datasets with Hill coefficients up to 4, Fig. 1 needs to be replaced by a tetramer model. The number of models/hypotheses then becomes large. A need for automated k - K model enumeration approaches is therefore anticipated.

Conclusions

Compared to single model fits of the empirical Hill model, fits of families of rational polynomials such as those presented here are preferable because they yield predictions that can guide subsequent experiments to elucidate mechanisms.

Methods

Data

All of the datasets were digitized using plotDigitizer [9]. The ATP concentrations in all of the datasets was 2.5 mM or higher (see Table 8) and at such concentrations TK1 is a tetramer [5]. It is thus assumed that such tetramers are loose dimers of tight dimers such that interactions within dimers dominate interactions between dimers. This notion has some support [10]. The highest enzyme concentration in any of the datasets was that of Birringer et al at 306 pM, and the lowest substrate concentration appears to have been 50 nM. Given the large gap between these concentrations, it is safe to assume that total substrate concentrations approximately equal free substrate concentrations; if this were not the case, total concentration constraint polynomials in the free concentrations [11] could instead have been used to model the data.

Model selection

The Akaike Information Criterion (AIC) is $2 * P - 2 * \log$ -likelihood [7] which, in the case of normally distributed errors, is $AIC = 2 * P + N * \log(2 \pi) + N * \log(SSE/N) + N$ where P is the number of estimated parameters (including the variance), N is the number of data points and SSE is the sum of squared errors. The small sample size corrected $AIC_c = AIC + 2 * P(P+1) / (N-P-1)$ was used for model comparisons, as recommended in [8], as this correction is significant at the small sample size of the data in Fig. 3 (in contrast, this correction is negligible at the $N = 100$ sample size of the simulated data of Fig. 2). ΔAIC_c is the difference between the AIC_c of a particular model and the best/lowest AIC_c of all models tested.

Parameter Estimates

The 95% confidence intervals of the parameter estimates of Eq. (29) were obtained using `nls` and `confint` of the statistical programming environment R [6], see Additional File 4.

Competing interests

TR has no competing interests.

Authors' contributions

TR performed the work and wrote the paper.

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Figures

Figure 1 – Possible states of an infinitely tightly bound asymmetric enzyme dimer

Figure 2 – Simulated data fits

Comparison of LQRP fits to hill model “data” simulated at different n values. The rows are models with 4, 3, 3, 3, 2 and 2 parameters, respectively. Models with $\Delta AIC_c < 15$ are indicated by an asterisk. Parameters are given in Table 2. For details see Additional File 1.

Figure 3 – V - α LQRP fits to the hTK1 data of Berringer et al [1]

Units are pmoles/min and μM . For details see Additional Files 2 and 3.

Figure 4 – Top 2 models of data of Berringer et al [1] and Frederiksen et al [2] pooled

Substrate concentrations where model predictions differ most are excellent conditions for subsequent model discrimination experiments. See Additional File 6.

Tables

Table 1 – LQRP k-K Models

These models were derived from Eq. (2) using constraints to eliminate at least 2 parameters

row	Eq	k ₁	k ₂	k ₃	K ₁	K ₂	K ₃	Numerator	Denominator
1 ^s	3	k ₁	k ₁	k ₃	K ₁	K ₁	K ₃	$2k_1 \frac{S}{K_1} + 2k_3 \frac{S^2}{K_1 K_3}$	$1 + 2 \frac{S}{K_1} + \frac{S^2}{K_1 K_3}$
2	3	k ₃	k ₂	k ₃	K ₁	K ₁	K ₃	$(k_3 + k_2) \frac{S}{K_1} + 2k_3 \frac{S^2}{K_1 K_3}$	$1 + 2 \frac{S}{K_1} + \frac{S^2}{K_1 K_3}$
3	3	k ₁	k ₃	k ₃	K ₁	K ₁	K ₃	$(k_1 + k_3) \frac{S}{K_1} + 2k_3 \frac{S^2}{K_1 K_3}$	$1 + 2 \frac{S}{K_1} + \frac{S^2}{K_1 K_3}$
4	3	k ₁	k ₁	k ₃	K ₁	K ₂	K ₁	$k_1 \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + 2k_3 \frac{S^2}{K_1^2}$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1^2}$
5	3	k ₃	k ₂	k ₃	K ₁	K ₂	K ₁	$\left(k_3 \frac{1}{K_1} + k_2 \frac{1}{K_2} \right) S + 2k_3 \frac{S^2}{K_1^2}$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1^2}$
6	3	k ₁	k ₃	k ₃	K ₁	K ₂	K ₁	$\left(k_1 \frac{1}{K_1} + k_3 \frac{1}{K_2} \right) S + 2k_3 \frac{S^2}{K_1^2}$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1^2}$
7	3	k ₁	k ₁	k ₃	K ₁	K ₂	K ₂	$k_1 \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{2k_3 S^2}{K_1 K_2}$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1 K_2}$
8	3	k ₃	k ₂	k ₃	K ₁	K ₂	K ₂	$\left(\frac{k_3}{K_1} + \frac{k_2}{K_2} \right) S + \frac{2k_3 S^2}{K_1 K_2}$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1 K_2}$
9	3	k ₁	k ₃	k ₃	K ₁	K ₂	K ₂	$\left(\frac{k_1}{K_1} + \frac{k_3}{K_2} \right) S + \frac{2k_3 S^2}{K_1 K_2}$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1 K_2}$
.10	4	k ₁ +k ₂ =2k ₃			K ₁	K ₁	K ₃	$2k_3 \left(\frac{S}{K_1} + \frac{S^2}{K_1 K_3} \right)$	$1 + 2 \frac{S}{K_1} + \frac{S^2}{K_1 K_3}$
11	11b	k ₁ +k ₂ =2k ₃			K ₁	K ₂	K ₁	$\left(\frac{k_1}{K_1} + \frac{k_2}{K_2} \right) S + (k_1 + k_2) \frac{S^2}{K_1^2}$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1^2}$
12	11b	k ₁ +k ₂ =2k ₃			K ₁	K ₂	K ₂	$\left(\frac{k_1}{K_1} + \frac{k_2}{K_2} \right) S + (k_1 + k_2) \frac{S^2}{K_1 K_2}$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1 K_2}$
13	4	k ₃	k ₃	k ₃	K ₁	K ₂	K ₃	$2k_3 \left(\left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1 K_3} \right)$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1 K_3}$
14 ^s	4	k ₃	k ₃	k ₃	K ₁	K ₁	K ₃	$2k_3 \left(\frac{S}{K_1} + \frac{S^2}{K_1 K_3} \right)$	$1 + 2 \frac{S}{K_1} + \frac{S^2}{K_1 K_3}$
15	4	k ₃	k ₃	k ₃	K ₁	K ₂	K ₁	$2k_3 \left(.5 \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1^2} \right)$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1^2}$
16	4	k ₃	k ₃	k ₃	K ₁	K ₂	K ₂	$2k_3 \left(.5 \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1 K_2} \right)$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S + \frac{S^2}{K_1 K_2}$

row	Eq	k_1	k_2	k_3	K_1	K_2	K_3	Numerator	Denominator
17	5	k_1	k_2	k_3	K_1	K_1	K_1	$\frac{k_1+k_2}{K_1}S + \frac{2k_3}{K_1^2}S^2$	$\left(1 + \frac{S}{K_1}\right)^2$
18 ^s	5	k_1	k_1	k_3	K_1	K_1	K_1	$\frac{2k_1}{K_1}S + \frac{2k_3}{K_1^2}S^2$	$\left(1 + \frac{S}{K_1}\right)^2$
19	5	k_3	k_2	k_3	K_1	K_1	K_1	$\frac{k_3+k_2}{K_1}S + \frac{2k_3}{K_1^2}S^2$	$\left(1 + \frac{S}{K_1}\right)^2$
20	5	k_1	k_3	k_3	K_1	K_1	K_1	$\frac{k_1+k_3}{K_1}S + \frac{2k_3}{K_1^2}S^2$	$\left(1 + \frac{S}{K_1}\right)^2$
21	8	k_3	k_3	k_3	K_1	K_1	K_1	$2k_3 \frac{S}{K_1}$	$1 + \frac{S}{K_1}$
22	3	X	k_2	k_3	∞	K_2	K_3	$\frac{k_2}{K_2}S + \frac{2k_3}{K_1K_3}S^2$	$1 + \frac{1}{K_2}S + \frac{S^2}{K_1K_3}$
23	4	X	k_3	k_3	∞	K_2	K_3	$2k_3 \left(\frac{.5}{K_2}S + \frac{1}{K_1K_3}S^2 \right)$	$1 + \frac{1}{K_2}S + \frac{S^2}{K_1K_3}$
24	3	X	k_2	k_3	∞	K_2	K_2	$\frac{k_2}{K_2}S + \frac{2k_3}{K_1K_2}S^2$	$1 + \frac{1}{K_2}S + \frac{S^2}{K_1K_2}$
25	4	X	k_3	k_3	∞	K_2	K_2	$2k_3 \left(\frac{.5}{K_2}S + \frac{1}{K_1K_2}S^2 \right)$	$1 + \frac{1}{K_2}S + \frac{S^2}{K_1K_2}$
26	3	k_1	X	k_3	K_1	∞	K_3	$\frac{k_1}{K_1}S + \frac{2k_3}{K_1K_3}S^2$	$1 + \frac{1}{K_1}S + \frac{S^2}{K_1K_3}$
27	4	k_3	X	k_3	K_1	∞	K_3	$2k_3 \left(\frac{.5}{K_1}S + \frac{1}{K_1K_3}S^2 \right)$	$1 + \frac{1}{K_1}S + \frac{S^2}{K_1K_3}$
28	6	k_1	X	k_3	K_1	∞	K_1	$\frac{k_1}{K_1}S + \frac{2k_3}{K_1^2}S^2$	$1 + \frac{1}{K_1}S + \frac{S^2}{K_1^2}$
29	7	k_3	X	k_3	K_1	∞	K_1	$2k_3 \left(\frac{.5}{K_1}S + \frac{1}{K_1^2}S^2 \right)$	$1 + \frac{1}{K_1}S + \frac{S^2}{K_1^2}$
30	8	k_1	k_2	X	K_1	K_2	∞	$\left(\frac{k_1}{K_1} + \frac{k_2}{K_2} \right) S$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S$
31	8	k_1	k_1	X	K_1	K_2	∞	$k_1 \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S$	$1 + \left(\frac{1}{K_1} + \frac{1}{K_2} \right) S$
32	8	k_1	k_2	X	K_1	K_1	∞	$\left(\frac{k_1+k_2}{K_1} \right) S$	$1 + \frac{2}{K_1}S$
33 ^s	8	k_1	k_1	X	K_1	K_1	∞	$k_1 \frac{2}{K_1}S$	$1 + \frac{2}{K_1}S$
34 ^s	9	X	X	k_3	∞	∞	K_3	$2k_3 \frac{S^2}{K_1K_3}$	$1 + \frac{S^2}{K_1K_3}$
35	8	X	k_2	X	∞	K_2	∞	$k_2 \frac{1}{K_2}S$	$1 + \frac{1}{K_2}S$

row	Eq	k_1	k_2	k_3	K_1	K_2	K_3	Numerator	Denominator
36	8	k_1	X	X	K_1	∞	∞	$k_1 \frac{1}{K_1} S$	$1 + \frac{1}{K_1} S$
37 ⁿ		X	X	X	∞	∞	∞	0	1

X = any finite value is acceptable since the parameter is not in the model

^S = models that assume a symmetric dimer, i.e. $K_1 = K_2$ and $k_1 = k_2$.

ⁿ = null model not mapped to an equation

Table 2 - Fits to simulated Hill data

EQ	n	SSE	AICc	α_1	V_∞	V_1	α_2	<n>
hill	0.4	0.02295	-233.55	1.2336	0.9189			0.4469
hill	0.7	0.02283	-233.81	1.1033	0.9685			0.736
hill	1.3	0.02269	-234.11	1.0557	0.9908			1.3382
hill	1.6	0.02267	-234.15	1.0482	0.9946			1.6436
eq3	0.4	0.02295	-231.07	14.255	0.753	9.999	19.809	
eq3	0.7	0.02274	-231.52	5.516	0.9	2.886	8.111	
eq3	1.3	0.02258	-231.88	0.551	1.006	0.453	1.238	
eq3	1.6	0.02252	-232.02	0.197	0.999	0.205	1.025	
eq4	0.4	0.0329	-215.53	5.087	1.02		0.877	
eq4	0.7	0.02431	-230.66	2.216	0.931		1.673	
eq4	1.3	0.02253	-234.46	0.479	0.997		1.055	
eq4	1.6	0.02252	-234.49	0.201	1		1.039	
eq5	0.4	0.08354	-168.94	4.777	0.662	3.161		
eq5	0.7	0.04897	-195.64	1.749	0.836	1.462		
eq5	1.3	0.02709	-225.24	2.261	1.054	0.041		
eq5	1.6	0.06048	-185.09	1.978	1.133	0		
eq6	0.4	0.14564	-141.15	6.615	0.631	1.168		
eq6	0.7	0.12868	-147.34	1.819	0.771	0.886		
eq6	1.3	0.02259	-234.32	1.118	1.007	0.454		
eq6	1.6	0.03091	-218.66	1.512	1.071	0		
eq18	0.4	0.08355	-168.94	2.387		3.161	0	
eq18	0.7	0.04897	-195.64	0.874		1.462	0	
eq18	1.3	0.04032	-205.36	0.263		0.754	0.02	
eq18	1.6	0.08575	-167.63	0.158		0.639	0.028	
eq19 ^a	0.4	0.08354	-168.94	17751663	0.662		1.7E+08	
eq19 ^a	0.7	0.04897	-195.64	16743770	0.836		58566375	
eq19	1.3	0.0268	-225.79	1.943	1.044		4.736	
eq19	1.6	0.02577	-227.75	0.394	1.032		1.787	
eq20 ^a	0.4	0.03585	-211.24	17463314	0.706		67178398	
eq20	0.7	0.0228	-233.87	7.35	0.895		11.949	
eq20	1.3	0.02306	-233.31	0.737	1.019		1.75	
eq20	1.6	0.02304	-233.34	0.269	1.016		1.287	
eq21 ^a	0.4	0.07465	-174.57	49.069	0.668		384.913	

eq21	0.7	0.03451	-213.15	21.285	0.853		58.981	
eq21	1.3	0.02256	-234.39	0.455	0.994		0.978	
eq21	1.6	0.02643	-226.48	0.118	0.952		0.563	
eq22	0.4	0.0231	-233.21	35.802	0.746		34.074	
eq22	0.7	0.0229	-233.65	5.481	0.908		4.705	
eq22	1.3	0.02411	-231.07	0.55	1.033		2.541	
eq22	1.6	0.03091	-218.66	0	1.071		2.286	
eq23	0.4	0.023	-233.42	23.289	0.757		0.645	
eq23	0.7	0.02365	-232.03	4.72	0.921		0.51	
eq23	1.3	0.04354	-201.53	1.084	1.093		2.98	
eq23	1.6	0.12038	-150.67	0.923	1.177		2.671	
eq7	0.4	0.14831	-142.61	5.232	0.63			
eq7	0.7	0.13026	-149.1	2.093	0.774			
eq7	1.3	0.02284	-236.16	1.011	1.005			
eq7	1.6	0.057	-190.42	0.889	1.073			
eq8	0.4	0.08354	-171.3	4.776	0.662			
eq8	0.7	0.04897	-198.01	1.749	0.836			
eq8	1.3	0.06972	-180.35	0.771	1.126			
eq8	1.6	0.17539	-134.22	0.659	1.215			
eq9	0.4	0.28491	-109.96	35.052	0.588			
eq9	0.7	0.35878	-98.44	6.448	0.702			
eq9	1.3	0.1178	-154.12	1.55	0.895			
eq9	1.6	0.0472	-199.85	1.215	0.952			
eq24	0.4	0.72007	-63.61	0.376		1.072		
eq24	0.7	0.33923	-101.24	0.25		0.795		
eq24	1.3	0.05783	-189.7	0.177		0.66		
eq24	1.6	0.08593	-169.89	0.166		0.647		
eq25	0.4	0.11167	-156.8	12.457	0.646			
eq25	0.7	0.10466	-160.04	5.026	0.796			
eq25	1.3	0.02714	-227.52	2.301	1.053			
eq25	1.6	0.06048	-187.46	1.978	1.133			
eq26	0.4	0.09286	-166.02	7.906	0.656			
eq26	0.7	0.06188	-186.32	2.969	0.823			
eq26	1.3	0.05104	-195.94	1.337	1.1			
eq26	1.6	0.13818	-146.14	1.151	1.183			
eq27	0.4	0.99154	-47.61	0.379		0.839		
eq27	0.7	0.51661	-80.21	0.265		0.651		
eq27	1.3	0.11481	-155.41	0.2		0.57		
eq27	1.6	0.10245	-161.11	0.191		0.566		
eq28	0.4	0.1487	-142.48	8.846	0.629			
eq28	0.7	0.16767	-136.47	3.717	0.765			
eq28	1.3	0.03519	-214.54	1.742	0.999			
eq28	1.6	0.03091	-221.02	1.512	1.071			

^aFits to these models did not converge.

Table 3 - LQRP fits to Birringer et al's 2006 data

EQ	SSE	AICc	α_1	V_∞	V_1	α_2	n
eq25	0.00026	-57.67	3.765	0.151			
eq28	0.00028	-56.93	2.756	0.145			
eq7	0.00029	-56.86	1.658	0.145			
eq26	0.00034	-55.35	2.316	0.156			
eq8	0.00039	-54.1	1.37	0.158			
eq22	0.00026	-50.48	0.833	0.148		6.732	
eq20	0.00027	-50.23	1.293	0.148		4.635	
eq9	0.00061	-49.99	3.645	0.132			
eq1	0.00028	-49.88	1.941	0.144			1.297
eq6	0.00028	-49.71	2.747	0.145	0		
eq4	0.00029	-49.6	0.815	0.146		2.704	
eq24	0.00065	-49.5	0.272		0.149		
eq21	3.00E-04	-49.33	1.459	0.149		3.996	
eq19	0.00032	-48.79	0.946	0.144		6.156	
eq23	0.00033	-48.49	2.145	0.155		3.006	
eq18	0.00037	-47.41	0.576		0.2	0.022	
eq5	0.00037	-47.25	0.96	0.157	0.207		
eq27	0.00105	-45.19	0.303		0.127		
eq3	0.00026	-38.57	2.5287	0.1496	0.0205	10.1832	

Table 4 - LQRP fits to Fredericksen et al's 2004 data

EQ	SSE	AICc	α_1	V_∞	V_1	α_2	n
eq25	0.65514	11.12	3.904	9.408			
eq7	0.79543	13.06	1.666	9.051			
eq28	0.92358	14.56	2.895	8.988			
eq26	1.05517	15.89	2.325	9.75			
eq5	0.65514	17.12	3.904	9.408	0		
eq19	0.65509	17.12	3.967	9.414		15.415	
eq22	0.68674	17.59	1.067	9.305		6.973	
eq20	0.7127	17.97	1.424	9.276		4.955	
eq1	0.71901	18.05	1.891	9.096			1.263
eq8	1.35414	18.38	1.366	9.925			
eq21	0.75662	18.56	1.083	9.247		3.199	
eq4	0.77582	18.81	0.92	9.167		2.643	
eq6	0.77785	18.84	2.002	9.068	5.973		
eq18	0.9075	20.38	0.501		11.706	0.028	
eq23	0.92916	20.62	1.852	9.71		5.483	
eq24	2.21962	23.33	0.238		8.575		
eq3	0.65156	26.07	6.0618	9.4465	-4.7865	23.7351	
eq9	2.95794	26.2	4.071	8.092			
eq27	4.128	29.53	0.256		7.132		

Table 5 - LQRP fits to Berenstein et al's 2000 data

EQ	SSE	AICc	α_1	V_∞	V_1	α_2	n
eq7	3.07179	26.96	1.708	16.921			
eq6	2.83282	29.57	1.255	16.798	16.794		
eq4	3.05477	30.7	0.899	16.946		2.919	
eq21	3.0714	30.78	0.843	16.915		2.89	
eq1	3.25408	31.65	2.014	16.881			1.275
eq20	3.53592	32.89	1.347	17.017		5.359	
eq25	4.63669	33.14	4.285	17.133			
eq3	2.77059	33.9	0.6384	16.8003	18.6378	1.2412	
eq22	3.89233	34.33	1.165	17.084		8.022	
eq28	5.05865	34.45	2.888	16.922			
eq26	5.55593	35.85	2.776	17.265			
eq5	4.50722	36.53	3.914	17.167	7.39		
eq19	4.57175	36.75	3.117	17.081		14.274	
eq23	5.23599	38.78	2.352	17.25		4.741	
eq18	5.35286	39.11	0.775		27.835	0.001	
eq8	6.92409	39.15	1.705	17.327			
eq9	13.69352	49.38	2.847	16.298			
eq24	288.1286	95.08	0.086		7.656		
eq27	388.9926	99.58	0.09		6.266		

Table 6 - LQRP fits to Li et al's 2004 data

EQ	SSE	AICc	α_1	V_∞	V_1	α_2	n
eq8	1.69566	18.58	1.898	11.308			
eq26	1.70185	18.63	3.122	11.241			
eq19	1.65183	22.25	48.183	11.279		188.884	
eq18	1.66414	22.36	0.925		21.133	0	
eq21	1.67467	22.45	3.855	11.278		11.83	
eq20	1.67714	22.47	3.468	11.278		10.291	
eq22	1.6785	22.48	3.482	11.277		9.574	
eq23	1.68202	22.51	3.521	11.277		2.269	
eq5	1.68475	22.53	2.679	11.274	19.822		
eq1	1.69224	22.59	1.917	11.288			1.011
eq4	1.69377	22.61	1.866	11.295		3.615	
eq25	2.4134	23.52	4.921	11.089			
eq3	1.67961	27.54	1.0873	11.3725	22.0115	0.3613	
eq7	3.50368	28.74	2.008	10.9			
eq28	4.26879	31.5	3.442	10.858			
eq6	3.48153	32.69	2.178	10.906	10.099		
eq9	13.16382	47.27	5.147	10.168			
eq24	106.5948	76.55	0.116		7.145		
eq27	142.0577	80.57	0.134		6.481		

Table 7 - LQRP fits to Munch-Petersen et al's 1993 data

EQ	SSE	AICc	α_1	V_∞	V_1	α_2	n
eq3	0.1502	-13.29	0.436	8.6199	9.3605	0.0764	
eq18	0.47862	0.89	0.495		10.324	0.003	
eq6	0.59866	4.47	0.792	9.159	7.024		
eq7	0.80163	5.51	1.259	9.374			
eq1	0.72345	7.5	1.33	9.394			1.237
eq4	0.74461	7.96	0.732	9.451		1.543	
eq21	0.78879	8.88	0.721	9.424		1.729	
eq20	0.92797	11.48	1.159	9.518		3.026	
eq25	1.25015	12.62	3.074	9.57			
eq22	1.00152	12.71	1.105	9.565		4.085	
eq26	1.29873	13.23	1.939	9.7			
eq5	1.12152	14.52	2.571	9.627	4.984		
eq23	1.23238	16.02	1.67	9.683		3.164	
eq19	1.24215	16.15	3.848	9.601		11.302	
eq28	1.59368	16.5	2.148	9.381			
eq8	1.64634	17.02	1.175	9.765			
eq9	4.40849	32.78	1.922	8.869			
eq24	30.12785	63.53	0.091		3.904		
eq27	44.92134	69.92	0.094		3.107		

Table 8 - Available Human Thymidine Kinase 1 data

dT	v	E_0	ATP	year	figure	first author
0.0917	0.012	306	6	2006	4a	Birringer
0.249	0.0282	306	6	2006	4a	Birringer
0.498	0.0709	306	6	2006	4a	Birringer
0.747	0.0862	306	6	2006	4a	Birringer
0.996	0.0883	306	6	2006	4a	Birringer
1.99	0.116	306	6	2006	4a	Birringer
3	0.133	306	6	2006	4a	Birringer
4.49	0.127	306	6	2006	4a	Birringer
5.99	0.143	306	6	2006	4a	Birringer
0.0699	0.342	200	2.5	2004	4a	Frederiksen
0.119	1.03	200	2.5	2004	4a	Frederiksen
0.214	1.92	200	2.5	2004	4a	Frederiksen
0.427	3.63	200	2.5	2004	4a	Frederiksen
0.846	5.81	200	2.5	2004	4a	Frederiksen
1.24	6.46	200	2.5	2004	4a	Frederiksen
1.65	6.49	200	2.5	2004	4a	Frederiksen
2.04	7.55	200	2.5	2004	4a	Frederiksen
4.05	8.76	200	2.5	2004	4a	Frederiksen
8.01	8.62	200	2.5	2004	4a	Frederiksen
0.04535	0.907	200	2.5	2000	2a	Berenstein
0.096983	2.25	200	2.5	2000	2a	Berenstein

0.197633	3.34	200	2.5	2000	2a	Berenstein
0.394156	6.07	200	2.5	2000	2a	Berenstein
0.802521	9.55	200	2.5	2000	2a	Berenstein
1.183486	12.9	200	2.5	2000	2a	Berenstein
1.587112	13.3	200	2.5	2000	2a	Berenstein
2.008547	14.1	200	2.5	2000	2a	Berenstein
4.047619	15.3	200	2.5	2000	2a	Berenstein
7.819905	16.5	200	2.5	2000	2a	Berenstein
16.1	16.9	200	2.5	2000	2a	Berenstein
24	16.4	200	2.5	2000	2a	Berenstein
40	16.7	200	2.5	2000	2a	Berenstein
79.9	17.6	200	2.5	2000	2a	Berenstein
120	16.1	200	2.5	2000	2a	Berenstein
0.075862	1.32	200	2.5	2004	2a	Li
0.035823	0.566	200	2.5	2004	2a	Li
0.198658	2.96	200	2.5	2004	2a	Li
0.314729	4.06	200	2.5	2004	2a	Li
0.402344	5.15	200	2.5	2004	2a	Li
0.806024	6.69	200	2.5	2004	2a	Li
1.007353	8.22	200	2.5	2004	2a	Li
1.202703	8.01	200	2.5	2004	2a	Li
1.638507	8.34	200	2.5	2004	2a	Li
2.01467	8.24	200	2.5	2004	2a	Li
9.72	10.8	200	2.5	2004	2a	Li
19.7	11.1	200	2.5	2004	2a	Li
49.7	11.6	200	2.5	2004	2a	Li
100	10.9	200	2.5	2004	2a	Li
0.051474	0.489	80	2.5	1993	4	Munch-Petersen
0.097841	0.861	80	2.5	1993	4	Munch-Petersen
0.201282	1.57	80	2.5	1993	4	Munch-Petersen
0.39749	2.85	80	2.5	1993	4	Munch-Petersen
0.589425	3.79	80	2.5	1993	4	Munch-Petersen
1.005871	5.14	80	2.5	1993	4	Munch-Petersen
2.026393	6.91	80	2.5	1993	4	Munch-Petersen
3.045455	8.04	80	2.5	1993	4	Munch-Petersen
4.033816	8.35	80	2.5	1993	4	Munch-Petersen
5.081395	8.74	80	2.5	1993	4	Munch-Petersen
5.933333	8.9	80	2.5	1993	4	Munch-Petersen
8.107143	9.08	80	2.5	1993	4	Munch-Petersen
12.37845	9.42	80	2.5	1993	4	Munch-Petersen
19.91091	8.94	80	2.5	1993	4	Munch-Petersen
27.90274	9.18	80	2.5	1993	4	Munch-Petersen
64.38849	8.95	80	2.5	1993	4	Munch-Petersen

Additional files

Additional file 1 – R script to generate Figure 2

This file can be sourced into R to recreate Figure 2 and Table 2.

Additional file 2 – Available TK1 Data

This is a tab delimited version of Table 8. It is read in by Additional Files 3-6.

Additional file 3 – R script to generate Figure 3

This R script can be sourced into R to generate Figure 3 and Table 3 to 7.

Additional file 4 – R script to generate parameter estimates of Eq. (29)

This R script generates Eq. (29) parameter estimates for the data of Birringer et al.

Additional file 5 – R script to normalize data

This R script amplitude normalizes the data in Additional File 2.

Additional file 6 – R script to generate Figure 4

This R script generates Figure 4.

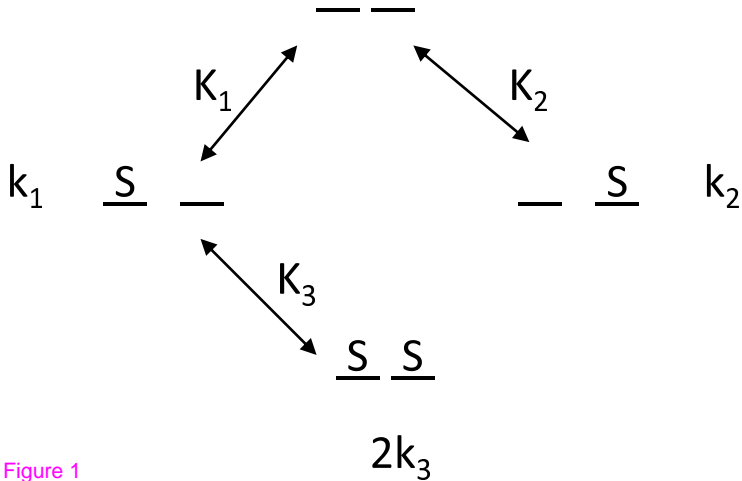


Figure 1

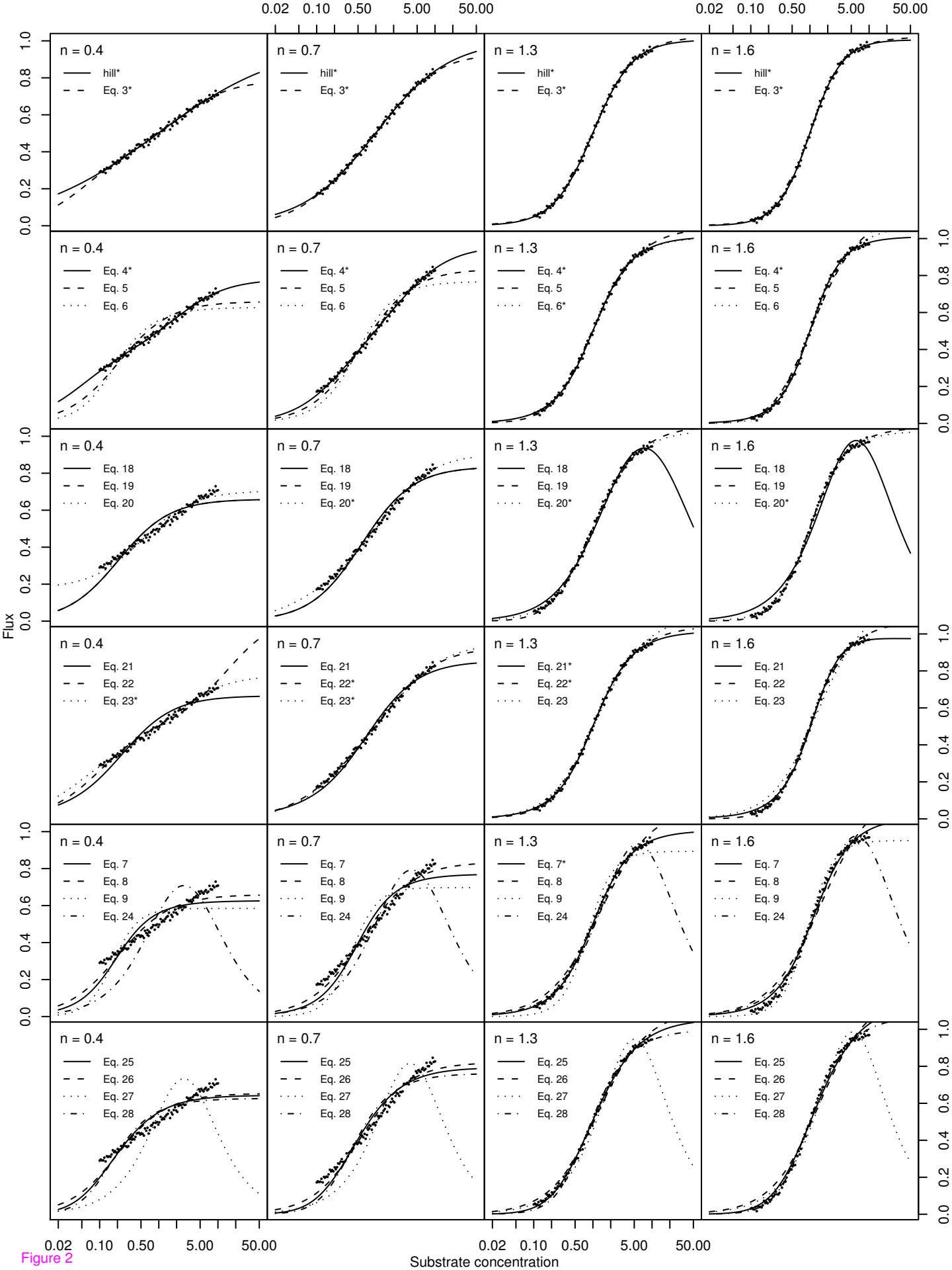


Figure 2

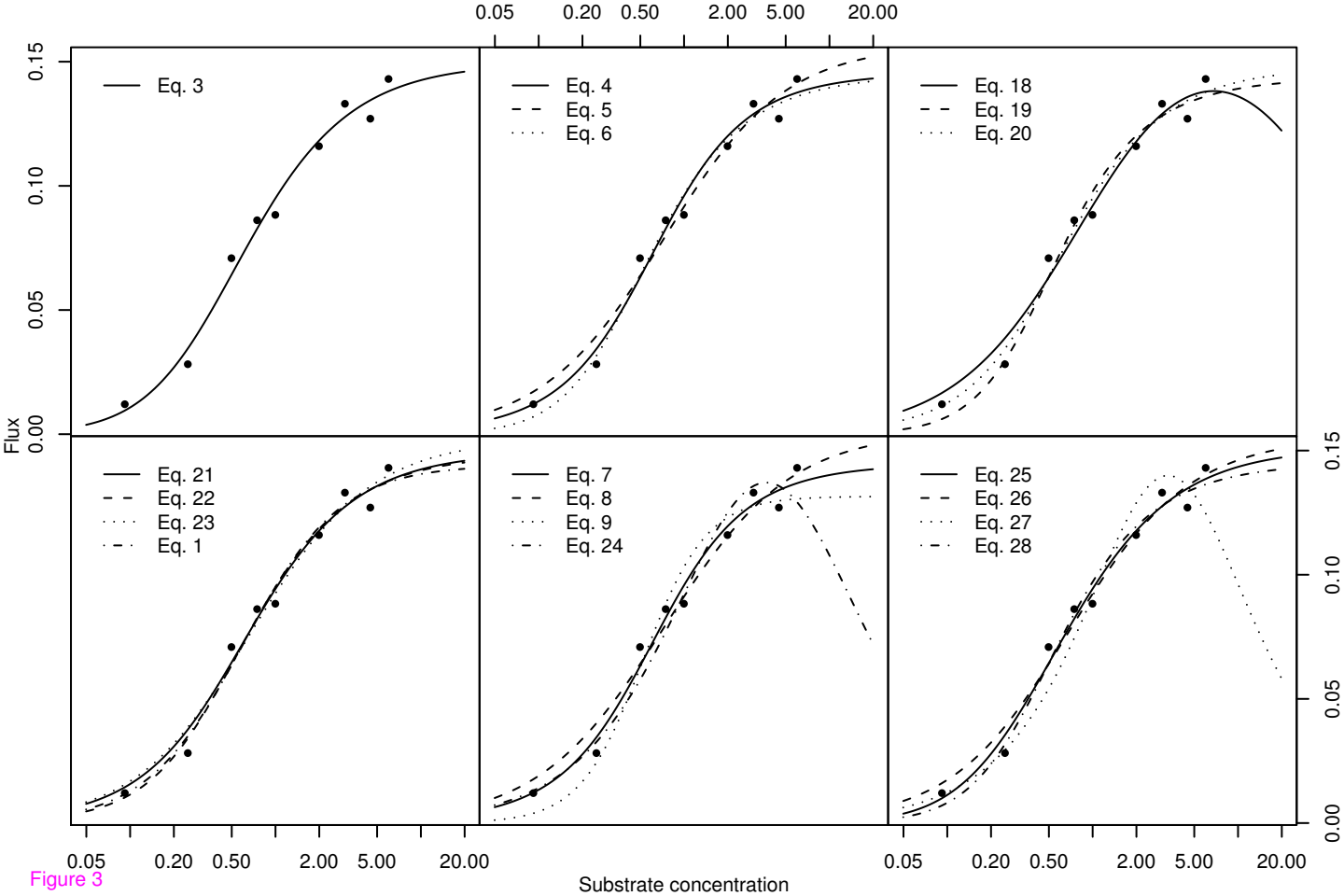


Figure 3

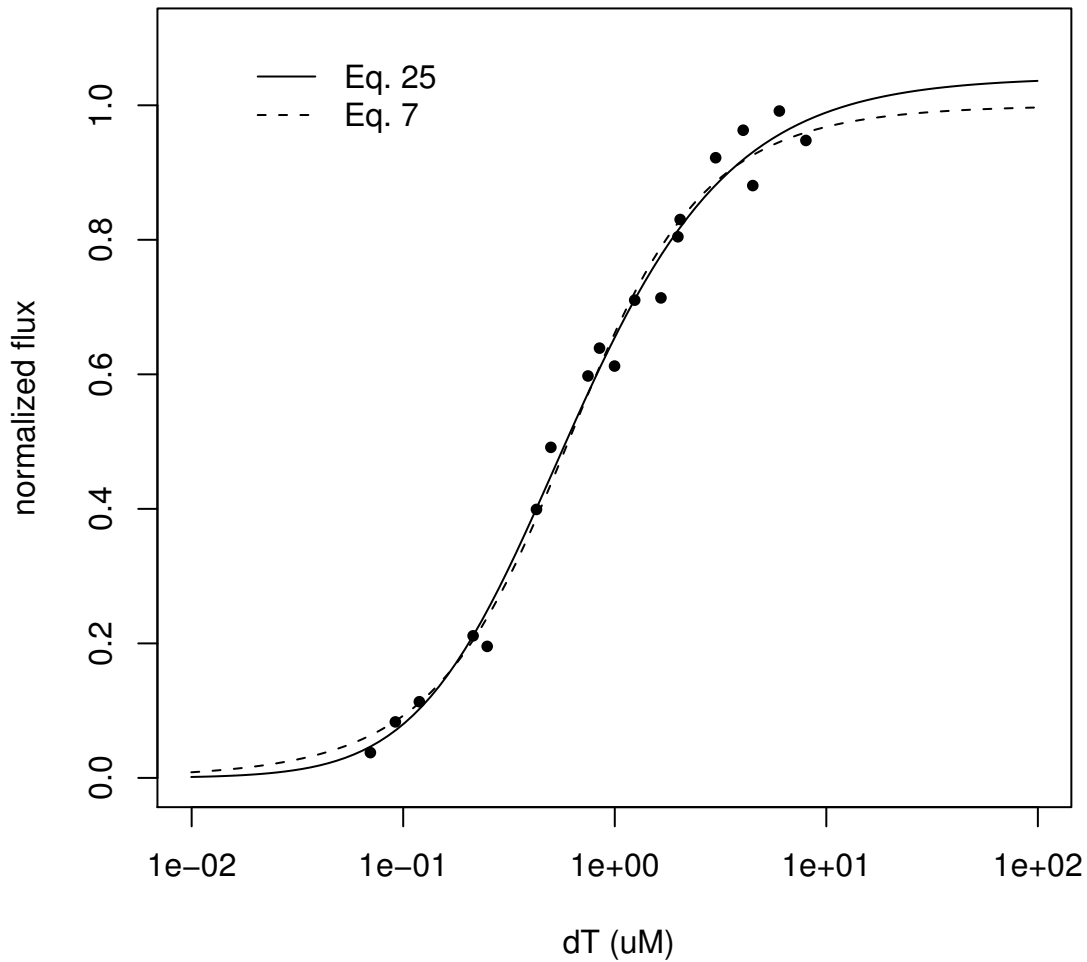


Figure 4

Additional files provided with this submission:

Additional file 1: addf1fithills.r, 7K

<http://www.biomedcentral.com/imedia/1541234632221165/supp1.r>

Additional file 2: addf2tk1.txt, 3K

<http://www.biomedcentral.com/imedia/8264360982211658/supp2.txt>

Additional file 3: addf3fitall.r, 7K

<http://www.biomedcentral.com/imedia/7156695992211658/supp3.r>

Additional file 4: addf4birreq29.r, 0K

<http://www.biomedcentral.com/imedia/2884002422116584/supp4.r>

Additional file 5: addf5mknorm.r, 2K

<http://www.biomedcentral.com/imedia/1173268833221165/supp5.r>

Additional file 6: addf6top2.r, 1K

<http://www.biomedcentral.com/imedia/1807485967221165/supp6.r>