

## Estimation of Parameters for RICHARDS Model

TATSURO AKAMINE<sup>1)</sup>

### Abstract

AKAMINE (1986)'s BASIC program by MARQUARDT's method was rewritten for RICHARDS model and its expanded model by the periodic function. For 0.9~1.1 the "LOG" function is corrected by TAYLOR series. Data estimated to be negative are cut off. AIC judges the effect of adding  $n$  to the parameters. RICHARDS model is not so important in practice but it is important theoretically.

**Key words** RICHARDS, MARQUARDT, TAYLOR series, AIC, BASIC program

### I. Introduction

AKAMINE (1986) estimated parameters by MARQUARDT's method for VON BERTALANFFY, logistic and GOMPertz models and their expanded models by the periodic function. RICHARDS model includes these three models. In this paper, estimation of parameters for RICHARDS model and correction of the "LOG" function in the calculation will be described.

### II. RICHARDS model

#### 1. Model

RICHARDS model is defined in the differential equation as follows :

$$\frac{dl}{dt} = Kl \left[ 1 - \left( \frac{l}{l_{\infty}} \right)^n \right] \quad (2.1)$$

Then let

$$v = \frac{\left( \frac{l_{\infty}}{l} \right)^n - 1}{n} \quad (2.2)$$

Therefore,

$$\frac{dv}{dt} = - \frac{l_{\infty}^n}{l^{n+1}} \frac{dl}{dt} \quad (2.3)$$

Received : October 13, 1987. Contribution A No. 447 from the Japan Sea Regional Fisheries Research Laboratory.

1) Japan Sea Regional Fisheries Research Laboratory, Suido-cho, Niigata, 951, Japan.

(〒951 新潟市水道町1丁目5939-22 日本海区水産研究所)

Substitution of (2.1) and (2.2) into (2.3) gives

$$-\frac{dv}{dt} = -Kv. \tag{2.4}$$

A general solution of this differential equation is

$$v = eh, \quad h = -Kt + c, \quad c : \text{integral constant.} \tag{2.5}$$

Substitution of (2.5) into (2.2) gives

$$l = \frac{l_\infty}{(1 + ne^h)^{\frac{1}{n}}}, \quad h = -Kt + c. \tag{2.6}$$

This is the general solution of RICHARDS model.

The initial condition :

$$\text{when } t = t_0, \quad l = \frac{l_\infty}{(1 + n)^{\frac{1}{n}}}. \tag{2.7}$$

gives the particular solution :

$$l = \frac{l_\infty}{(1 + ne^h)^{\frac{1}{n}}}, \quad h = -K(t - t_0). \tag{2.8}$$

On the other hand, the initial condition :

$$\text{when } t = 0, \quad l = l_0 \tag{2.9}$$

gives the particular solution :

$$l = \frac{l_\infty}{\{1 + (p^n - 1)e^h\}^{\frac{1}{n}}}, \quad p = \frac{l_\infty}{l_0}, \quad h = -Kt. \tag{2.10}$$

Note that

$$\lim_{n \rightarrow \infty} \left(1 + \frac{x}{n}\right)^n = \lim_{n \rightarrow 0} (1 + nx)^{\frac{1}{n}} = e^x, \tag{2.11}$$

$$\lim_{n \rightarrow 0} \frac{y^n - 1}{n} = \ln y. \tag{2.12}$$

Then (2.8) corresponds to three models as follows :

$$\begin{cases} n = -1 : \text{VON BERTALANFFY model} \\ n \rightarrow 0 : \text{GOMPertz model} \\ n = 1 : \text{logistic model} \end{cases}$$

Relation of  $t_0$  and  $l_0$  is

$$t_0 = \frac{1}{K} \ln \frac{p^n - 1}{n}, \quad \text{when } n \rightarrow 0, \quad t_0 = \frac{1}{K} \ln(\ln p). \tag{2.13}$$

Although (2.9) is more general than (2.7) as an initial condition, (2.7) is usually used in fishery population dynamics and is easier to treat in calculation. (2.13) combines (2.8) and (2.10).

2. Property

Setting  $l''=0$ , we find that

$$1-(n+1)\left(\frac{l}{l_\infty}\right)^n=0. \tag{2.14}$$

When  $n > -1$ , this equation has a solution corresponding to (2.7). Namely, when  $n > -1$ ,  $t_0$  is an inflection point.

Outlines of this model are as follows : First, (2.10) gives

$$\lim_{n \rightarrow \infty} l = l_0, \tag{2.15}$$

$$\lim_{n \rightarrow -\infty} l = \begin{cases} l_0 & (t = 0) \\ l_\infty & (t > 0) \end{cases} \tag{2.16}$$

These are shown in Fig. 1. On the other hand, (2.8) gives

$$\lim_{n \rightarrow \infty} l = l_\infty, \tag{2.17}$$

$$\lim_{n \rightarrow -\infty} l = \begin{cases} 0 & (t = t_0') \\ l_\infty & (t > t_0') \end{cases}, \quad t_0' = t_0 + \frac{\ln(-n)}{K}. \tag{2.18}$$

Namely, (2.8) has intersection  $t_0'$  with the transverse axis ( $l=0$ ) when  $n < 0$ . These are shown in Fig. 2. When  $n < 0$ , (2.8) is rewritten as

$$l = l_\infty(1 - e^{h})^m, \quad h = -K(t - t_0'), \quad m = -\frac{1}{n}. \tag{2.8'}$$

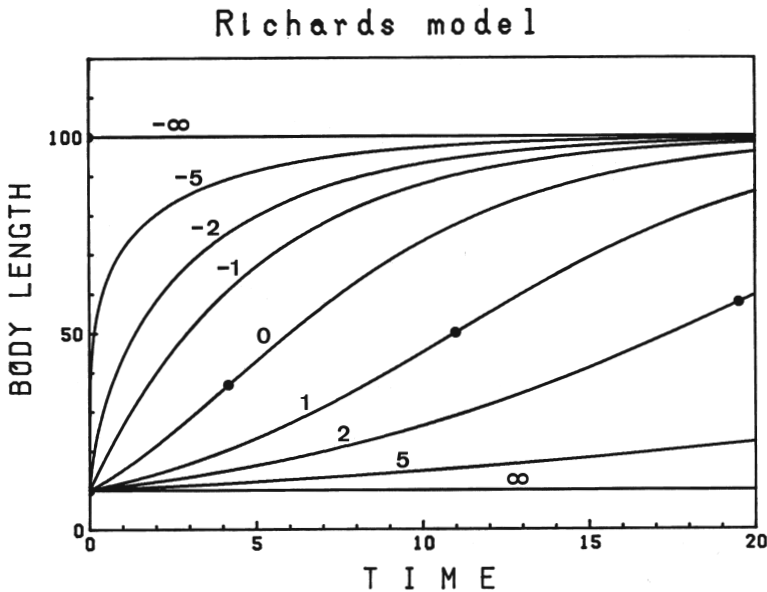


Fig. 1. RICHARDS model :  $l = \frac{l_\infty}{1 + (p^n - 1)e^{ht}}$ ,  $p = \frac{l_\infty}{l_0}$ ,  $h = -Kt$ .  
 $l_\infty = 100$ ,  $K = 0.2$ ,  $l_0 = 10$ ,  $n = -\infty, -5, -2, -1, 0, 1, 2, 5, \infty$ .

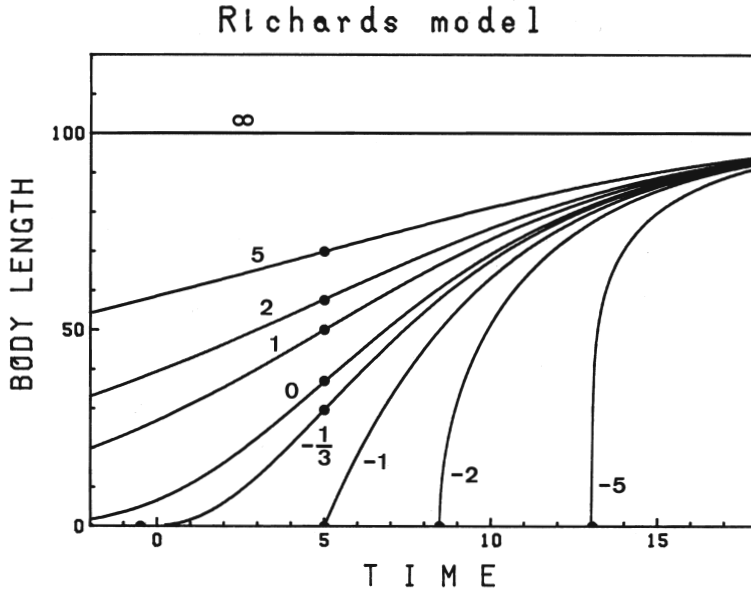


Fig. 2. RICHARDS model :  $l = \frac{l_{\infty}}{(1+ne^{ht})^{\frac{1}{n}}}$ ,  $h = -K(t-t_0)$ .  
 $l_{\infty}=100, K=0.2, t_0=5, n=-5, -2, -1, -1/3, 0, 1, 2, 5, \infty$ .

This is called the generalized VON BERTALANFFY model. Specifically, it is generally used as a body weight growth model when  $n=-1/3$ .

3. Expanded model by the periodic function

This expansion is defined as follows :

$$K \rightarrow Kf(t), \quad f(t+1) = f(t) \tag{2.19}$$

AKAMINE (1986) presented two models defined as follows in (2.4) :

$$\frac{dv}{dt} = -Kf(t)v \quad (\text{type-1}) \tag{2.20}$$

$$\frac{dv}{dt} = -Kf(t)e^{ht} \quad (\text{type-2}) \tag{2.21}$$

In this paper, only the type-1 model is discussed because the type-1 is more natural than the type-2. The particular solution of (2.20) with the initial condition as (2.7) is

$$l = \frac{l_{\infty}}{(1+ne^{hF(t)})^{\frac{1}{n}}}, \quad h = -K\{F(t)-F(t_0)\}, \quad F'(t) = f(t). \tag{2.22}$$

AKAMINE (1986) used the following periodic function.

$$f(t) = \frac{1+a}{2} + \frac{1-a}{2} \cos 2\pi(t-t_1) \tag{2.23}$$

$$F(t) = \frac{1+a}{2} t + \frac{1-a}{4\pi} \sin 2\pi(t-t_1) \quad (2.24)$$

The inflection points are given by the following equation.

$$h'^2(1-e^h) + h''(1+ne^h) = 0 \quad (2.25)$$

This equation is the general equation of equation (33), (53) and (63) of AKAMINE (1986) and can be solved by NEWTON'S method.

### III. Estimation of parameters

#### 1. MARQUARDT'S method

This is the expanded NEWTON'S method. Let  $Y$  be the objective function,  $\theta$  be parameters. It is expressed as follows in the case of searching the minimal point.

$$(\mathbf{H} + \lambda \mathbf{I}) \Delta \theta = \mathbf{g}, \quad \mathbf{H} = \left( -\frac{\partial^2 Y}{\partial \theta_i \partial \theta_j} \right), \quad \mathbf{g} = -\frac{\partial Y}{\partial \theta}. \quad (3.1)$$

$\mathbf{H}$  : Hessian matrix

$\mathbf{I}$  : unit matrix

$\mathbf{g}$  : gradient vector

$\lambda$  is the control factor of convergence. When  $\lambda \rightarrow \infty$  it approaches the steepest descent method :  $\Delta \theta = (1/\lambda)\mathbf{g}$ . On the other hand, when  $\lambda \rightarrow 0$  it approaches NEWTON'S method :  $\mathbf{H}\Delta \theta = \mathbf{g}$ . Therefore, let  $\lambda$  be large at first, and make it small step by step to get the solution. In this paper, the simplest method is used. When  $\Delta Y < 0$  let  $\lambda^{\text{new}} = \lambda^{\text{old}}/2$  to continue the calculation, when  $\Delta Y \geq 0$  let  $\lambda^{\text{new}} = \lambda^{\text{old}} * 2$  and try again the same iterative routine. When  $\Delta Y \geq 0$  after 10 times enlarging  $\lambda$  continuously, we determine it to be the solution to end the calculation.

Scaling of the parameters is necessary because MARQUARDT'S method is like to the steepest descent method at first. Scaling is defined by a diagonal matrix  $\mathbf{S}$ . Then (3.1) becomes

$$(\mathbf{S}^{-1}\mathbf{H}\mathbf{S}^{-1} + \lambda \mathbf{I}) \mathbf{S} \Delta \theta = \mathbf{S}^{-1}\mathbf{g}.$$

Cleaning this equation, we have

$$(\mathbf{H} + \lambda \mathbf{S}^2) \Delta \theta = \mathbf{g}. \quad (3.2)$$

Generally, we use

$$\mathbf{S}^2 = \text{diag} \mathbf{H}. \quad (3.3)$$

$\text{diag} \mathbf{A}$  : diagonal matrix composed of only the diagonal elements of  $\mathbf{A}$

Then it is sufficient to enlarge the diagonal elements of  $\mathbf{H}$  by a factor  $(1+\lambda)$ . If  $\mathbf{H}$  has a negative part of its diagonal elements, let  $\lambda > 1$  and enlarge that part by a factor  $(\lambda-1)$  and the other part by a factor  $(1+\lambda)$ .

The objective function is the weighted least-squares method

$$Y = \sum_{k=1}^N \left( \frac{l - l_k^\circ}{\sigma_k^\circ} \right)^2. \tag{3.4}$$

$N$  : number of data

$l_k^\circ, \sigma_k^\circ$  : data

Then it leads to

$$\frac{\partial Y}{\partial l} = \sum_k \frac{2(l - l_k^\circ)}{\sigma_k^{\circ 2}}, \quad \frac{\partial^2 Y}{\partial l^2} = \sum_k \frac{2}{\sigma_k^{\circ 2}}, \tag{3.5}$$

$$\frac{\partial^2 Y}{\partial \theta_i \partial \theta_j} = \frac{\partial^2 Y}{\partial l^2} \frac{\partial l}{\partial \theta_i} \frac{\partial l}{\partial \theta_j} + \frac{\partial Y}{\partial l} \frac{\partial^2 l}{\partial \theta_i \partial \theta_j}. \tag{3.6}$$

Because the second term of (3.6) contributes a little, it is omitted generally. Then we get

$$\frac{\partial^2 Y}{\partial \theta_i \partial \theta_j} \approx \frac{\partial^2 Y}{\partial l^2} \frac{\partial l}{\partial \theta_i} \frac{\partial l}{\partial \theta_j} = \sum_{k=1}^N \frac{2}{\sigma_k^{\circ 2}} \frac{\partial l}{\partial \theta_i} \frac{\partial l}{\partial \theta_j}. \tag{3.7}$$

Therefore, the diagonal elements of  $\mathbf{H}$  are always positive.

## 2. Partial differentiation by parameters

Parameters of RICHARDS model (2.8) and (2.22) are  $l_\infty, K, t_0, t_1, a$  and  $n$ . Concrete expressions of  $\partial l / \partial \theta$  are as follows :

$$\frac{\partial l}{\partial l_\infty} = \frac{l}{l_\infty}. \tag{3.8}$$

$$\frac{\partial l}{\partial \theta} = -l \frac{e^h}{1 + ne^h} \frac{\partial h}{\partial \theta}, \quad \theta = K, t_0, t_1, a. \tag{3.9}$$

Where for (2.8)

$$\frac{\partial h}{\partial K} = -(t - t_0)$$

$$\frac{\partial h}{\partial t_0} = K.$$

Where for (2.22)

$$\frac{\partial h}{\partial K} = -\{F(t) - F(t_0)\}$$

$$\frac{\partial h}{\partial t_0} = Kf(t_0)$$

$$\frac{\partial h}{\partial t_1} = -K \left\{ \frac{\partial F(t)}{\partial t_1} - \frac{\partial F(t_0)}{\partial t_1} \right\}$$

$$\frac{\partial F(t)}{\partial t_1} = -\frac{1-a}{2} \cos 2\pi(t - t_1)$$

$$\frac{\partial h}{\partial a} = -K \left\{ \frac{\partial F(t)}{\partial a} - \frac{\partial F(t_0)}{\partial a} \right\}$$

$$\frac{\partial F(t)}{\partial a} = \frac{1}{2} t - \frac{1}{4\pi} \sin 2\pi(t - t_1).$$

For  $n$

$$\frac{\partial l}{\partial n} = l \frac{1}{n} \left\{ \frac{1}{n} \ln(1+nx) - \frac{x}{1+nx} \right\} > 0, \quad x = e^h. \quad (3.10)$$

$$\lim_{n \rightarrow 0} \frac{\partial l}{\partial n} = l \frac{x^2}{2} > 0.$$

The sign of (3.10) is apparent in Fig. 2.

### 3. Correction of the “LOG” function

When  $n \rightarrow 0$  it is difficult to calculate (2.8), (2.22) and (3.10) precisely. When we use a high precision computer, it is sufficient to be careful only for  $n=0$ . The probability of  $n$  being 0 is so low for normal data that we can ignore this case. But, when we use a low precision computer, this problem is important because the precision of its “LOG” function is too low.

TAKAHASHI (1974) and HITOTSUMATSU (1981) suggested that computers treat the calculation of power as follows :

$$x^y \rightarrow \text{EXP}(y * \text{LOG}(x)).$$

Although the “EXP” function is high precision, the “LOG” function is low precision. The values of  $\ln(1+n)$  for a personal computer PC9801F (NEC, N<sub>88</sub>-BASIC) and a hand-held calculator FX502P (CASIO) are shown in Table 1. The FX502P result is correct and the PC9801F result is not correct because of TAYLOR series as follows :

$$\ln(1+z) = z - \frac{z^2}{2} + \frac{z^3}{3} - \frac{z^4}{4} + \frac{z^5}{5} - \dots \quad (3.11)$$

**Table 1.** Values of LOG(1+n) for PC9801F (NEC) and FX502P (CASIO).

$n$	PC9801F	FX502P
100000	11.5129	11.51293546
10000	9.21044	9.210440367
1000	6.90875	6.908754779
100	4.61512	4.615120516
10	2.3979	2.397895272
1	0.693147	0.69314718
0.1	$9.53102 \times 10^{-2}$	$9.5310179 \times 10^{-2}$
0.01	$9.95025 \times 10^{-3}$	$9.950330853 \times 10^{-3}$
0.001	$9.99446 \times 10^{-4}$	$9.995003330 \times 10^{-4}$
$10^{-4}$	$9.99405 \times 10^{-5}$	$9.999500033 \times 10^{-5}$
$10^{-5}$	$9.91555 \times 10^{-6}$	$9.999950000 \times 10^{-6}$
$10^{-6}$	$9.08925 \times 10^{-7}$	$9.999995000 \times 10^{-7}$
$10^{-7}$	$8.26296 \times 10^{-8}$	$9.999999500 \times 10^{-8}$
$10^{-8}$	0	$9.999999950 \times 10^{-9}$
$10^{-9}$	0	$9.999999995 \times 10^{-10}$

And (3.10) has the problem of cancellation. Let

$$a = \frac{1}{n} \ln(1+nx), \quad b = \frac{x}{1+nx}.$$

When  $n=0.1$ ,  $x=0.005$  it is as follows :

	PC9801F	FX502P
$a$	4.99826	4.998750416
$b$	4.9975	4.997501249
$a - b$	0.00076	0.001249167

Thus, the PC9801F gives the wrong values. When  $n$  is small, the number of significant figures drop even in the FX502P values.

In this paper, for (2.8) and (2.22) the following expression is used by (3.11).

$$(1+nx)^{\frac{1}{n}} = \exp \left[ x \left\{ 1 - \frac{nx}{2} + \frac{(nx)^2}{3} - \frac{(nx)^3}{4} + \dots \right\} \right] \quad (3.12)$$

And for (3.10) the following expression is used by (3.11) and

$$\frac{1}{1+z} = 1 - z + z^2 - z^3 + z^4 - \dots \quad (3.13)$$

$$\frac{\partial l}{\partial n} = l \frac{x^2}{2} \left\{ 1 - \frac{2 \cdot 2nx}{3} + \frac{2 \cdot 3(nx)^2}{4} - \frac{2 \cdot 4(nx)^3}{5} + \dots \right\},$$

$$x = e^h. \quad (3.14)$$

(3.12) and (3.14) are used when  $|nx| \leq 0.1$ .

#### IV. AIC

When we treat  $n$  as a parameter the number of parameters increases by 1. Therefore, the likelihood increases. But, the confidence area will be enlarged because the correlations of parameters increase. An adequate number of parameters will be presented by AIC (AKAIKE information criterion) :

$$AIC = -2 \ln L_{\max} + 2r \quad (4.1)$$

$L_{\max}$  : maximum likelihood

$r$  : number of parameters

For the weighted least-squares method (3.4),  $(l_k - l_k^0) / \sigma_k^0$  distributes according to  $N(0, 1)$ . Then it leads to

$$L = \prod_{k=1}^N P_k = \left( \frac{1}{\sqrt{2\pi}} \right)^N \exp \left( -\frac{1}{2} Y \right), \quad (4.2)$$

$$AIC = Y_{\min} + 2r + \text{const.} \quad (4.3)$$

On the other hand, for the least-squares method :



$$Y^* = \sum_{k=1}^N (l - l_k^\circ)^2 \quad (4.4)$$

$(l_k - l_k^\circ)$  distributes according to  $N(0, \sigma)$ . Then it leads to

$$L = \left( \frac{1}{\sqrt{2\pi} \sigma} \right)^N \exp \left( -\frac{1}{2} \frac{Y^*}{\sigma^2} \right). \quad (4.5)$$

The following is used for the  $\sigma^2$  estimate.

$$\sigma^2 = \frac{Y^*_{\min}}{N-r} \quad (4.6)$$

Then it leads to

$$\text{AIC} = N \ln Y^*_{\min} + 2r + \text{const.} \quad (4.7)$$

Where the following approximation is used.

$$\ln \left( 1 - \frac{r}{N} \right) \doteq -\frac{r}{N} \quad (r \ll N)$$

The model which minimizes AIC is regarded as the best. Namely, the model which explains the data efficiently with fewer parameters is regarded as best. Generally, AIC may be useful in the condition  $r \leq 2\sqrt{N}$ .

## V. Computer program

The BASIC programs for PC9801F (NEC) are listed in Appendices B and C. These are the only changing parts from AKAMINE (1986)'s program 1. When  $n < 0$ , the data satisfying  $1 + ne^h \leq 0$  are cut off. This is not so important in practice. After line 20000 there is a correction to the "LOG" function. This is not necessary for high precision computers or languages. It is better to check the "LOG" function before use.

## VI. Experiments

AKAMINE (1986)'s data (Table 2) is used for the test of these programs and results are shown in Table 3. Adding  $n$  to the parameters makes  $Y_{\min}$  smaller but AIC larger. Namely, it is not efficient for these data. It is natural because they are made for  $n = -1, 0$  and  $1$ . On the other hand, adding  $t_1$  and  $a$  to the parameters makes AIC smaller. They relate only to oscillation.

## Acknowledgements

The author is indebted to Mr. K. ISHIOKA of Tokai Regional Fisheries Research Laboratory and Mr. F. KATO of Seikai Regional Fisheries Research Laboratory for their kind advice and help. The author is also grateful to Mr. K. NOGAMI and Dr.

K. TANAKA of Japan Sea Regional Fisheries Research Laboratory for their critical reading of the manuscript.

**Table 2-a.** The data for the experiment (data-1).

$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$	$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$	$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$
1	0.5	5	3	8	2.0	47	2	15	3.5	80	3
2	0.8	12	3	9	2.2	54	3	16	4.0	82	2
3	1.0	18	2	10	2.4	63	3	17	4.5	87	3
4	1.2	30	4	11	2.5	66	3	18	5.0	88	3
5	1.3	36	3	12	2.8	69	3	19	7.5	99	5
6	1.5	42	3	13	3.0	68	6	20	10.0	99	2
7	1.7	45	3	14	3.2	74	3				

**Table 2-b.** The data for the experiment (data-2).

$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$	$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$	$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$
1	-4.0	1	2	10	-0.7	38	4	19	2.0	87	3
2	-3.5	3	2	11	-0.3	39	5	20	2.3	92	4
3	-3.0	4	3	12	0.0	48	4	21	2.8	93	3
4	-2.8	7	3	13	0.3	61	4	22	3.0	96	3
5	-2.4	7	3	14	0.6	62	4	23	3.5	97	2
6	-2.0	13	4	15	0.8	66	5	24	4.0	98	3
7	-1.7	17	3	16	1.0	75	4	25	5.0	99	3
8	-1.4	18	3	17	1.3	81	3				
9	-1.0	25	4	18	1.7	82	3				

**Table 2-c.** The data for the experiment (data-3).

$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$	$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$	$k$	$t_k$	$l_k^\circ$	$\sigma_k^\circ$
1	-1.3	1	3	8	0.2	50	2	15	2.0	88	2
2	-1.0	8	3	9	0.4	55	3	16	2.3	92	3
3	-0.8	16	2	10	0.7	56	5	17	2.7	92	3
4	-0.5	19	3	11	1.0	67	3	18	3.0	94	3
5	-0.3	24	3	12	1.2	77	3	19	4.0	98	2
6	-0.1	29	4	13	1.5	81	2	20	5.0	98	3
7	0.0	40	4	14	1.8	82	3				

Table 3. Results of experiments. Comparison with AKAMINE (1986).

	Number of iterations	$I_{\infty}$	$K$	$t_0$	$t_1$	$a$	$n$	$Y_{\min}$	$r^{th}$	AIC <sup>b)</sup>
data-1	0	100	.5	.5	.25	0	-1			
	3	99.9635	.507699	.558275	—	(1)	(-1)	15.7711 <sup>c)</sup>	3	21.7711
	6	100.139	.496821	.504319	—	(1)	-1.03834	15.7461 <sup>c)</sup>	4	23.7461
	5	100.623	.870266	.388283	.229144	.119223	(-1)	3.93503	5	13.93503
	10	100.225	.906215	.475398	.223683	.124174	-.929432	3.81993	6	15.81993
data-2	0	100	1.0	0	0	0	0			
	4	99.1726	.993326	-.080152	—	(1)	(0)	17.8405	3	23.8405
	7	99.1302	.997562	-.075764	—	(1)	-.008186	17.8391	4	25.8391
	9	99.7023	1.94285	-.014149	.006776	.015631	(0)	2.65882	5	12.65882
	9	99.4431	2.0074	-.002191	.007257	.011215	.058150	2.60802	6	14.60802
data-3	0	100	1.0	0	0	0	1			
	5	99.7154	1.00196	-.003079	—	(1)	(1)	7.28418	3	13.27418
	5	99.949	.975934	-.028745	—	(1)	.938929	7.25647	4	15.25647
	7	99.7416	2.13245	.010413	.014517	.050024	(1)	1.27517	5	11.27517
	7	99.868	2.10076	.003795	.014613	.049559	.966074	1.26659	6	13.26659

a) number of parameters

b)  $AIC = Y_{\min} + 2r$ c)  $k=1$  data is cut off.

References

AKAMINE, T. (1986) Expansion of growth curves using a periodic function and BASIC programs by MARQUARDT's method. *Bull. Jap. Sea Reg. Fish. Res. Lab.*, (36), 77-107.  
 HITOTSUMATSU, S. (1981) 教室に電卓を！ II. pp 13-36, 海鳴社, 東京, 190 pp.  
 TAKAHASHI, H. (1974) ミニ電卓の“完全犯罪”. pp 64-71, In 数理の散策. 日本評論社, 東京, 155 pp.

RICHARDS の式のパラメータ推定

赤 嶺 達 郎

AKAMINE (1986) の MARQUARDT 法の BASIC プログラムを RICHARDS の式およびその周期関数による拡張式用書き換えた。0.9~1.1において TAYLOR 級数で“LOG”関数の修正を行った。推定値が負となるデータは除外した。n をパラメータに加える事の妥当性を AIC で判定した。RICHARDS の式は応用上はあまり重要ではないが、理論上重要である。

Appendix A. Partial differentiation by n for (2.10).

This is as follows :

$$\frac{\partial l}{\partial n} = l \frac{1}{n} \left[ \frac{1}{n} \ln \{1 + (p^n - 1)x\} - \frac{xp^n \ln p}{1 + (p^n - 1)x} \right] < 0, \quad x = e^h.$$

$$\lim_{n \rightarrow 0} \frac{\partial l}{\partial n} = -(\ln p)^2 \frac{x - x^2}{2} < 0.$$

The sign is apparent in Fig. 1. These expressions seem to be more difficult to treat than (3.10). The expression of  $n \rightarrow 0$  is led by (3.11), (3.13) and

$$\lim_{n \rightarrow 0} \frac{\frac{y^n - 1}{n} - \ln y}{n} = \frac{(\ln y)^2}{2}.$$

In addition to

$$\lim_{n \rightarrow 0} \frac{e^x - (1 + nx)^{\frac{1}{n}}}{n} = \frac{e^x x^2}{2}.$$

These are led by the following theory :

$$\text{When } \lim_{n \rightarrow a} f = 0 \text{ and } \lim_{n \rightarrow a} g = 0, \quad \lim_{n \rightarrow a} \frac{f}{g} = \lim_{n \rightarrow a} \frac{f'}{g'}.$$

**Appendix B.** The BASIC program to estimate parameters for RICHARDS model. Changing parts from program-1 of AKAMINE (1986).

```

10      '-----
20      '   Richards model by Marquardt's method
30      '
40      '               by Tatsuro Akamine
50      '                   1987-06-24
60      '-----
1085     '-----
1090     '   Definition of functions
1095     '-----
1100     NP=4
1110     DEF FNEP1=EXP(-P2(2)*(TIME(K)-P2(3)))
1115     DEF FNEP2=1+P2(4)*FNEP1
1120     DEF FNDP1=1/POWER9
1130     DEF FNBL =P2(1)*FNDP1
1140     DEF FNDP2=FNBL*FNEP1/FNEP2*(TIME(K)-P2(3))
1150     DEF FNDP3=-FNBL*FNEP1/FNEP2*P2(2)
1190     DEF FNDP4=FNBL*DLDN9
1200     DEF FNPC9801=FNEP2^(1/P2(4))
1210     DEF FNPC9802=(LOG(FNEP2)/P2(4)-FNEP1/FNEP2)/P2(4)
4072     '-----
4073     '   Check for 1+nx>0 and correction
4074     '-----
4075     IF FNEP2<=0 THEN PRINT "CANCEL 2 I=";K : GOTO *CSKIP2
4078     GOSUB *CHECK1
4105     GOSUB *CHECK2
4106     DIFFER(4)=FNDP4
4160     NEXT J : NEXT I
4163     *CSKIP2
4165     NEXT K
6023     IF FNEP2<=0 THEN LPRINT "CANCEL 1 I=";K : GOTO *CSKIP1
6025     GOSUB *CHECK1
6035     *CSKIP1
8065     PRINT "   Richards  n   =" ;P(4)
19985     '-----
19990     '   Correction of (1+nx)^(1/n) and dl/dn
19995     '-----
20000     *CHECK1
20010     BRANCH=P2(4)*FNEP1
20020     IF ABS(BRANCH)>.1 THEN POWER9=FNPC9801 ELSE GOSUB *CORRECT1
20030     RETURN
20100     *CHECK2
20110     BRANCH=P2(4)*FNEP1
20120     IF ABS(BRANCH)>.1 THEN DLDN9=FNPC9802 ELSE GOSUB *CORRECT2
20130     RETURN
21000     *CORRECT1
21010     CORY1=-BRANCH
21020     CORI1=2 : CORD1=1
21030     *CORSTART1
21040     CORC1=CORY1/CORI1
21050     IF ABS(CORC1)<.0000001 THEN *COREND1
21060     CORD1=CORD1+CORC1
21070     CORY1=CORY1*(-BRANCH) : CORI1=CORI1+1
21080     GOTO *CORSTART1
21090     *COREND1
21100     POWER9=EXP(FNEP1*CORD1)
21110     RETURN
22000     *CORRECT2
22010     CORY2=-BRANCH
22020     CORI2=3 : CORD2=1
22030     *CORSTART2
22040     CORC2=2*CORY2*(CORI2-1)/CORI2
22050     IF ABS(CORC2)<.0000001 THEN *COREND2
22060     CORD2=CORD2+CORC2
22070     CORY2=CORY2*(-BRANCH) : CORI2=CORI2+1
22080     GOTO *CORSTART2
22090     *COREND2
22100     DLDN9=FNEP1*FNEP1*CORD2/2
22110     RETURN

```

**Appendix C.** The BASIC program to estimate parameters for RICHARDS model expanded by a periodic function. Changing parts from appendix B.

```

10      '-----
20      '      Richards model expanded by periodic function
30      '      by Marquardt's method
40      '
50      '                                by Tatsuro Akamine
60      '                                1987-06-25
60      '-----
1020    PAI=3.14159265#
1100    NP=6
1110    DEF FNEP1=EXP(-P2(2)*(FNFT1(TIME(K))-FNFT1(P2(3))))
1115    DEF FNEP2=1+P2(4)*FNEP1
1120    DEF FNDP1=1/POWER9
1130    DEF FNBL =P2(1)*FNDP1
1140    DEF FNDP2=FNEP3*(FNFT1(TIME(K))-FNFT1(P2(3)))
1150    DEF FNDP3=-FNEP3*P2(2)*FNFT3(P2(3))
1190    DEF FNDP4=FNBL*DLN9
1200    DEF FNDP5=FNEP3*P2(2)*(FNFT4(TIME(K))-FNFT4(P2(3)))
1210    DEF FNDP6=FNEP3*P2(2)*(FNFT5(TIME(K))-FNFT5(P2(3)))
1300    DEF FNEP3=FNBL*FNEP1/FNEP2
1400    DEF FNFT1(TM)=FNP51*TM+FNP52/2/PAI*SIN(FNTM1(TM))
1410    DEF FNFT3(TM)=FNP51+FNP52*COS(FNTM1(TM))
1420    DEF FNFT4(TM)=-FNP52*COS(FNTM1(TM))
1430    DEF FNFT5(TM)=TM/2-1/4/PAI*SIN(FNTM1(TM))
1450    DEF FNP51=(1+P2(6))/2
1460    DEF FNP52=(1-P2(6))/2
1470    DEF FNTM1(TM)=2*PAI*(TM-P2(5))
4102    DIFFER(5)=FNDP5
4103    DIFFER(6)=FNDP6
8066    PRINT "          T1      =" ;P(5)
8067    PRINT "          A        =" ;P(6)

```