



Nonlinear curve for predicting height

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1. Introduction

In this example we consider the fitting of a double exponential model to the simulated height measurements of 130 females between the ages of 2 and 22. Data are given in **fem_height.lsf** and the data for the first female are shown below.

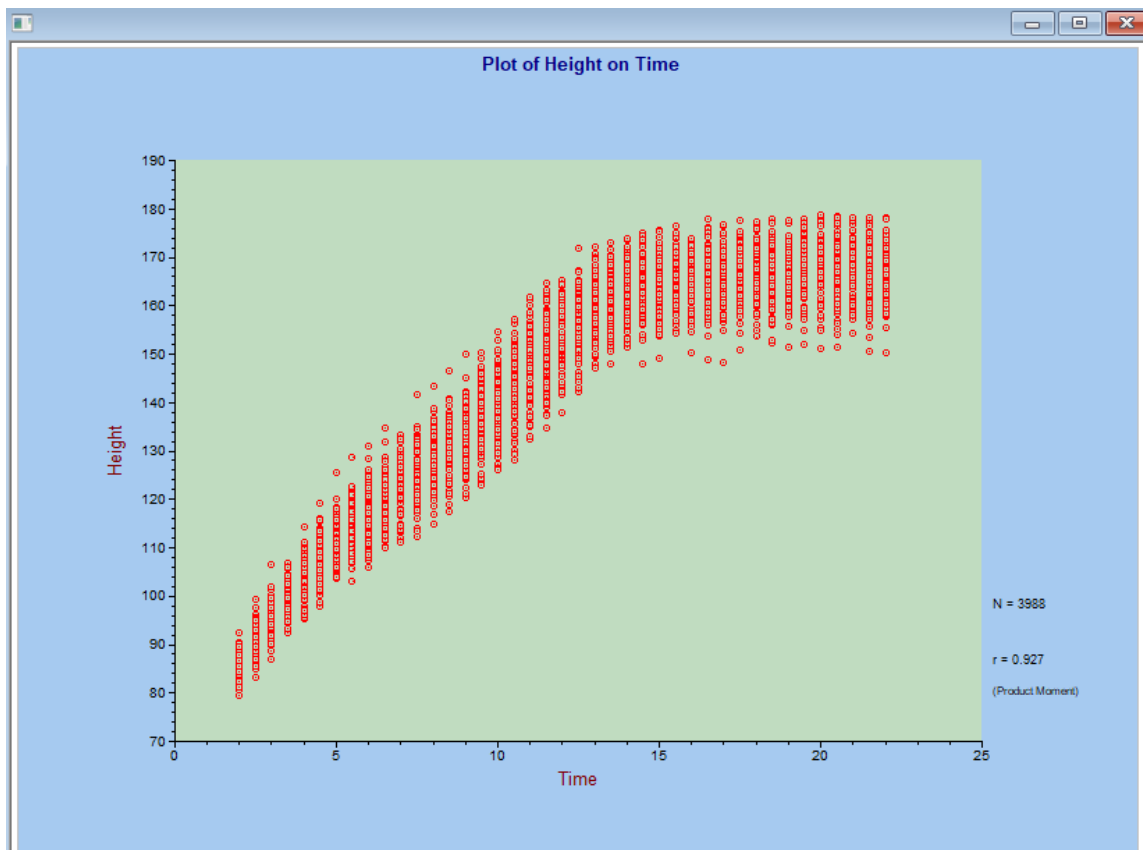
	Case	Occasio	Height	Time
1	1.00	1.00	86.53	2.00
2	1.00	2.00	92.23	2.50
3	1.00	3.00	96.90	3.00
4	1.00	4.00	99.52	3.50
5	1.00	5.00	103.62	4.00
6	1.00	6.00	106.90	4.50
7	1.00	9.00	117.96	6.00
8	1.00	11.00	122.87	7.00
9	1.00	12.00	125.01	7.50
10	1.00	15.00	132.84	9.00
11	1.00	16.00	137.01	9.50
12	1.00	18.00	146.28	10.50
13	1.00	19.00	148.23	11.00
14	1.00	20.00	150.66	11.50
15	1.00	21.00	158.22	12.00
16	1.00	22.00	157.99	12.50
17	1.00	23.00	160.56	13.00
18	1.00	24.00	162.91	13.50
19	1.00	25.00	163.04	14.00
20	1.00	26.00	165.88	14.50
21	1.00	27.00	166.08	15.00
22	1.00	28.00	166.00	15.50
23	1.00	29.00	168.56	16.00
24	1.00	30.00	167.60	16.50
25	1.00	31.00	168.32	17.00
26	1.00	32.00	167.68	17.50
27	1.00	33.00	169.96	18.00
28	1.00	34.00	168.21	18.50
29	1.00	38.00	169.22	20.50

The variables of interest are:

- Case: the identifier of each individual
- Occasio: the measurement occasion
- Height: the height of the individual at that point in time
- Time: the time of measurement (in years)

Note that not all individuals had complete data over the time period: some individuals had only 26 measurements, while others had up to 35 measurements.

A scatterplot of the height measurements over time is shown below. The relationship between height and time curve is nonlinear. Moreover, the curve shows two inflection points, at approximately 6 and again at approximately 13 years of age. While a nonlinear curve like the logistic curve has a single inflection point, multiple inflection points are best handled by fitting multiple component curves.



2. Double logistic curve

We now fit a double logistic curve to these data. The 3988 observations, nested within 130 level-2 units, were simulated according to the following model:

$$y = b_1 / (1 + s * \exp(b_2 - b_3 * time)) + c_1 / (1 + s * \exp(c_2 - c_3 * time)) + e$$

The level-2 model is:

$$b_1 = \beta_1 + u_1$$

$$b_2 = \beta_2 + u_2$$

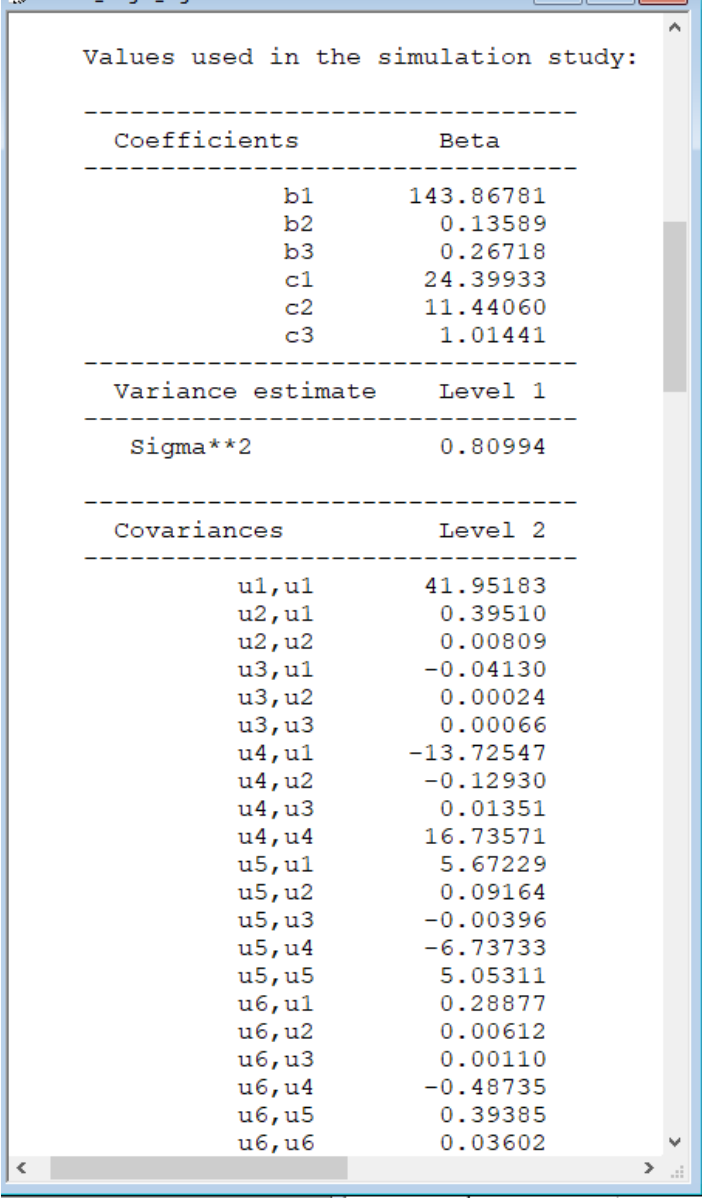
$$b_3 = \beta_3 + u_3$$

$$c_1 = \beta_3 + u_3$$

$$c_2 = \beta_4 + u_4$$

$$c_3 = \beta_5 + u_5$$

The data values used in the simulation study were:



Values used in the simulation study:

Coefficients		Beta
b1		143.86781
b2		0.13589
b3		0.26718
c1		24.39933
c2		11.44060
c3		1.01441

Variance estimate	Level 1
Sigma**2	0.80994

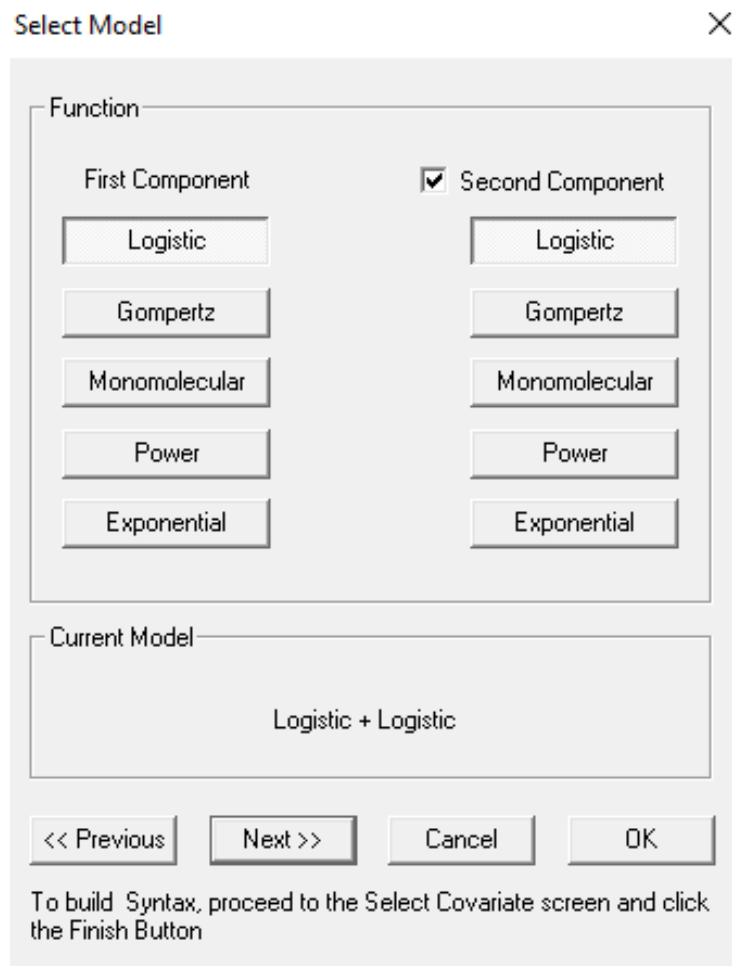
Covariances		Level 2
u1,u1		41.95183
u2,u1		0.39510
u2,u2		0.00809
u3,u1		-0.04130
u3,u2		0.00024
u3,u3		0.00066
u4,u1		-13.72547
u4,u2		-0.12930
u4,u3		0.01351
u4,u4		16.73571
u5,u1		5.67229
u5,u2		0.09164
u5,u3		-0.00396
u5,u4		-6.73733
u5,u5		5.05311
u6,u1		0.28877
u6,u2		0.00612
u6,u3		0.00110
u6,u4		-0.48735
u6,u5		0.39385
u6,u6		0.03602

The constant s assumes a value of 1 in this case, as we are simulating a monotonically increase in function value over time.

The syntax file for this model is shown in the syntax file **female_height_dlog.prl**. The variable **Case** is used as level-2 identifier (ID2).

```
female_height_dlog.prl
OPTIONS METHOD = ML CONVERGE = 0.000010 MAXITER = 30 QUADPTS = 8;
TITLE = Double Logistic Curve fitted to male female height measurements ;
SY=fem_height.lsf;
ID1 = Occasio;
ID2 = Case;
RESPONSE = Height;
FIXED = Time;
MODEL = Logistic + Logistic;
```

The Model statement, specifying the fitting of a double logistic model, corresponds to the setting shown below on the **Select Model** dialog box accessed via the **Multilevel, Nonlinear Regression** option from the main menu bar.



The data summary at the top of the output file shows the number of measurements for each individual.

```
o-----o
| DATA SUMMARY |
o-----o
NUMBER OF LEVEL 2 UNITS :      130
NUMBER OF LEVEL 1 UNITS :     3988
```

N2 :	1	2	3	4	5	6	7	8
N1 :	30	32	32	34	33	29	27	28
N2 :	9	10	11	12	13	14	15	16
N1 :	29	31	35	35	30	29	30	30
N2 :	17	18	19	20	21	22	23	24
N1 :	29	32	31	30	30	31	25	27
N2 :	25	26	27	28	29	30	31	32
N1 :	32	32	35	30	36	33	34	32
N2 :	33	34	35	36	37	38	39	40
N1 :	32	33	34	28	29	28	33	29
N2 :	41	42	43	44	45	46	47	48
N1 :	33	33	30	30	31	26	32	30
N2 :	49	50	51	52	53	54	55	56
N1 :	30	37	29	29	32	29	32	29
N2 :	57	58	59	60	61	62	63	64
N1 :	31	30	30	31	29	26	29	30
N2 :	65	66	67	68	69	70	71	72
N1 :	30	35	30	26	33	28	33	30
N2 :	73	74	75	76	77	78	79	80
N1 :	27	27	31	29	32	31	28	31
N2 :	81	82	83	84	85	86	87	88
N1 :	28	38	30	33	31	36	26	30
N2 :	89	90	91	92	93	94	95	96
N1 :	28	35	33	33	32	34	29	33
N2 :	97	98	99	100	101	102	103	104
N1 :	34	32	35	29	26	28	28	29
N2 :	105	106	107	108	109	110	111	112
N1 :	31	27	27	34	33	30	33	33
N2 :	113	114	115	116	117	118	119	120
N1 :	31	33	31	28	29	34	26	30
N2 :	121	122	123	124	125	126	127	128
N1 :	29	28	29	32	32	29	29	29
N2 :	129	130						
N1 :	32	31						

The ML solution is as follows.

Coefficients	Beta	Std.Err.	Z-value	P > z
b1	144.40476	0.46107	313.19687	0.00000
b2	0.14259	0.00597	23.87648	0.00000
b3	0.26813	0.00203	131.82791	0.00000
c1	23.73397	0.31387	75.61814	0.00000
c2	11.94765	0.17745	67.32993	0.00000
c3	1.07374	0.01567	68.50994	0.00000

Variance estimate	Level 1	Std.Err.	Z-value	P > z
Sigma**2	0.81292	0.01299	62.57296	0.00000

Covariances	Level 2	Std.Err.	Z-value	P > z
u1,u1	38.97579	4.67259	8.34136	0.00000
u2,u1	0.41023	0.05336	7.68757	0.00000
u2,u2	0.00770	0.00081	9.55870	0.00000
u3,u1	-0.02083	0.01525	-1.36594	0.17196
u3,u2	0.00031	0.00019	1.60376	0.10877
u3,u3	0.00062	0.00009	6.90328	0.00000
u4,u1	-11.92541	2.61176	-4.56605	0.00000
u4,u2	-0.12552	0.03236	-3.87904	0.00010
u4,u3	0.00637	0.01032	0.61779	0.53671
u4,u4	13.07078	2.02315	6.46060	0.00000
u5,u1	3.78622	1.36343	2.77698	0.00549
u5,u2	0.06869	0.01826	3.76096	0.00017
u5,u3	-0.00400	0.00575	-0.69525	0.48690
u5,u4	-4.99289	1.01919	-4.89889	0.00000
u5,u5	4.26683	0.64978	6.56659	0.00000
u6,u1	0.22012	0.11774	1.86948	0.06156
u6,u2	0.00508	0.00159	3.20148	0.00137
u6,u3	0.00076	0.00049	1.55961	0.11885
u6,u4	-0.40599	0.08906	-4.55861	0.00001
u6,u5	0.34800	0.05602	6.21217	0.00000
u6,u6	0.03323	0.00506	6.56378	0.00000

Note: ML estimates of individual coefficients written to file THETA1.EST

The beta coefficients reported correspond closely to the values used in simulation.

The average expected height can be estimated using the formula

$$\text{Predicted}(y) = 144.40476 / (1 + \exp(0.14259 - 0.26813 * \text{time})) + 23.73397 / (1 + \exp(11.94765 - 1.07374 * \text{time}))$$

The program also writes the estimated parameters for each level-2 unit to an external text file named **thetai.est**. The contents of this file for the first 10 individuals are as follows:

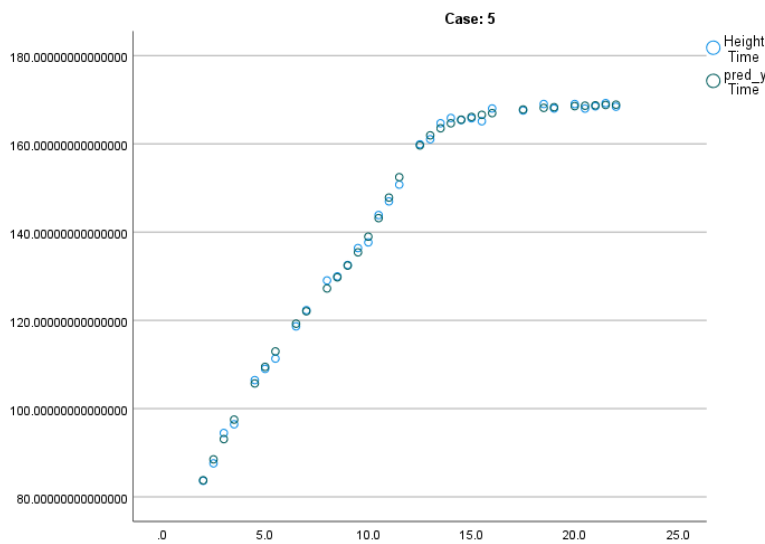
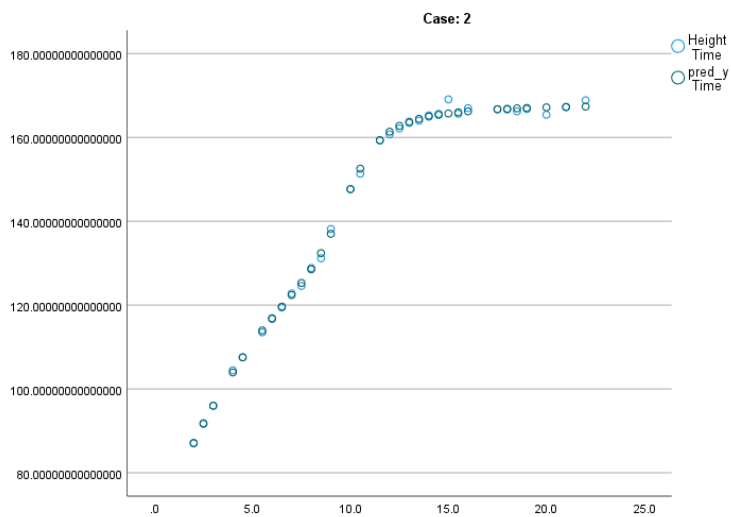
145.697	0.106036	0.252350	24.8169	10.3294	0.936850
137.712	0.351840E-01	0.289583	29.9058	11.2767	1.16088

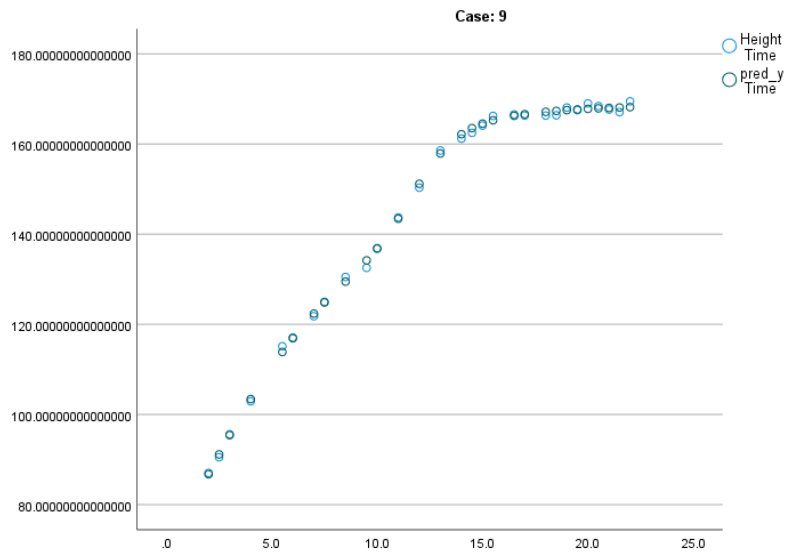
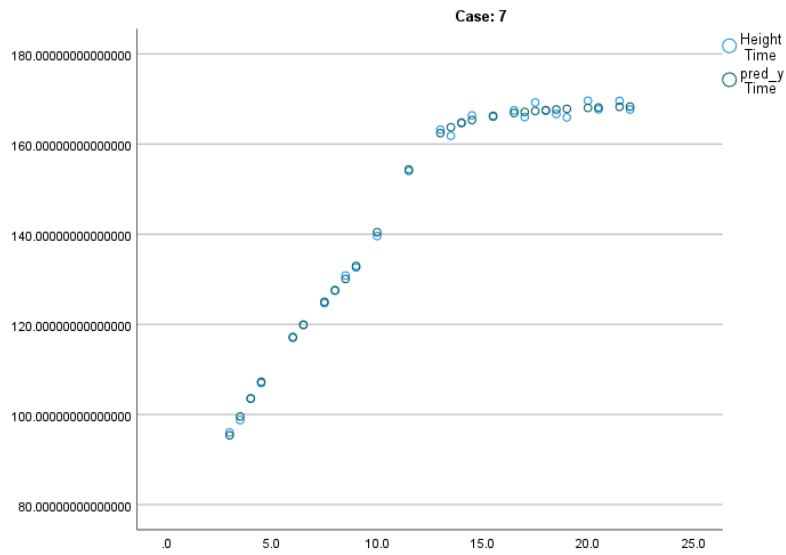
151.878	0.245825	0.270150	22.6760	13.9883	1.20602
147.849	0.185450	0.286616	24.8404	11.6040	1.15765
144.589	0.223534	0.271927	24.7484	13.0989	1.18217
144.996	0.149754	0.240066	19.3311	14.7623	1.21151
142.750	0.111284	0.270447	25.9821	12.6334	1.17554
145.235	0.150234	0.284730	25.9831	11.8968	1.12066
144.719	0.112014	0.257510	24.0276	11.7931	1.00305
128.401	-0.122994E-01	0.259993	23.5280	10.2627	0.967023

Using these results, the predicted height of, for example, the third female can be expressed as:

$$\text{Predicted}(y) = 151.878 / (1 + \exp(0.245825 - 0.270150 * \text{time})) + 22.6760 / (1 + \exp(13.9883 - 1.20602 * \text{time}))$$

When the observed and predicted heights for a few selected individuals are plotted, we see that the fitted curve describes the data well, even at the end of the period where there is more variation in the observed height over time.





3. Model misspecification

In this case, we know the model under which these data were simulated. However, if we did not, we might have opted to specify a single logistic model to describe these data. Looking at the original and estimated parameters in the previous section, we note that the parameter for c_1 is considerably smaller than for b_1 . It may thus be worth looking into whether one logistic component would do a reasonable job describing these data.

We modify the Model statement to

```
MODEL = Logistic;
```


For this model, the final results are

Coefficients	Beta	Std.Err.	Z-value	P > z
b1	175.04940	0.38201	458.23536	0.00000
b2	0.44204	0.00420	105.28139	0.00000
b3	0.19440	0.00141	138.26832	0.00000

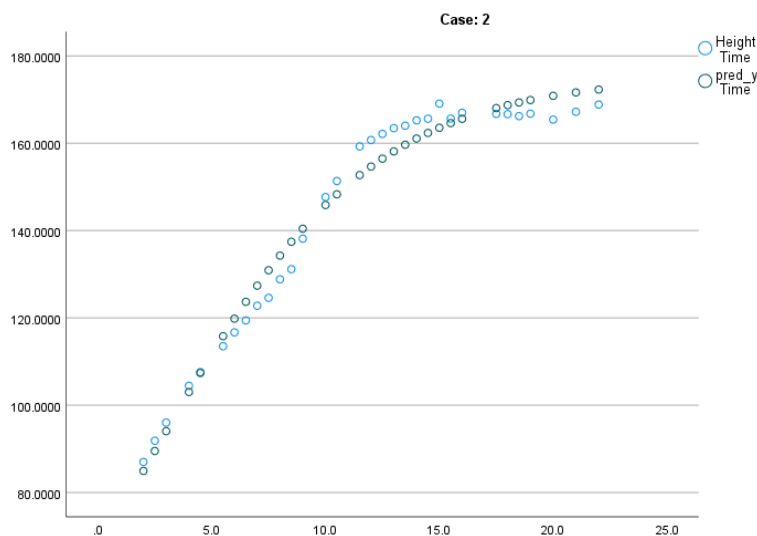
Variance estimate	Level 1	Std.Err.	Z-value	P > z
Sigma**2	8.74898	0.13928	62.81444	0.00000

Covariances	Level 2	Std.Err.	Z-value	P > z
u1,u1	34.18790	3.31490	10.31341	0.00000
u2,u1	0.16624	0.02724	6.10382	0.00000
u2,u2	0.00260	0.00040	6.51151	0.00000
u3,u1	-0.03681	0.00920	-4.00065	0.00006
u3,u2	0.00003	0.00010	0.29646	0.76688
u3,u3	0.00040	0.00004	8.94734	0.00000

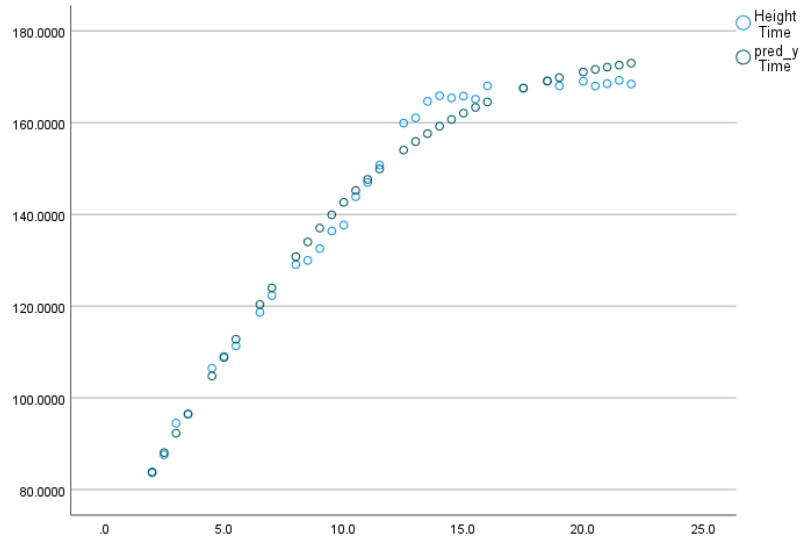
Under this model, the average predicted height can be calculated as

$$\text{Predicted}(y) = 175.0494 / (1 + \exp(0.44204 - 0.1944 * \text{time}))$$

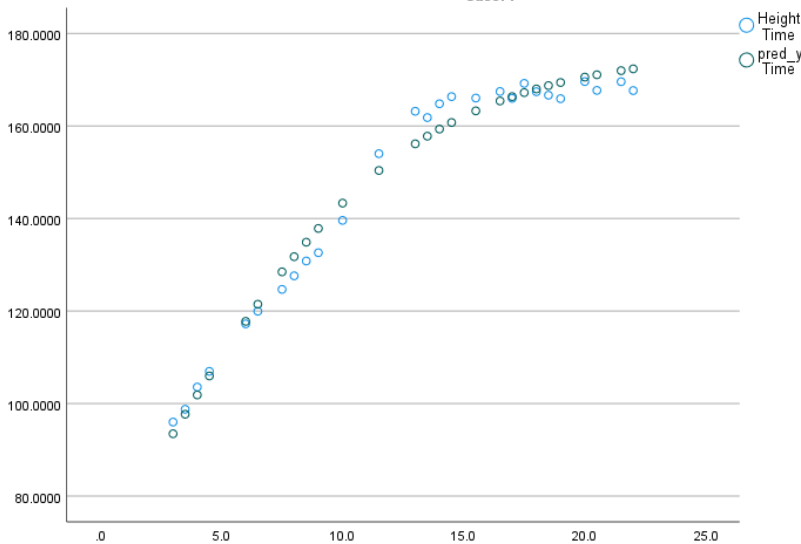
If we again use the information in the additional output file **thetai.est**, we can plot the observed and predicted height for the same individuals previously considered. When we consider the scatterplots for these individuals, we see that although the basic shape of the fitted curve closely mimics that of the “observed” data, it overestimates the first inflection in the data, underestimates the second, and in general produce a higher than observed final weight. We thus conclude that while it may seem as if this model describes the data reasonably well, the second logistic component is really needed in this case where the data has two inflection points.



Case: 5



Case: 7



Case: 9

