A Functional Analysis of Ultradian Activity in Laboratory Mice

Agnès GUILLOT and Jean-Arcady MEYER - URA 686-CNRS
Ecole Normale Supérieure, 46 rue d'Ulm, 75230 Paris cedex 05, France

Abstract

The ultradian alternation of rest/activity periods displayed by 10 C3H mice in diurnal condition, and by 10 others in nocturnal conditions, were compared with simulated sequences that respectively optimized three functional criteria, i.e. energy input, energy output, and net energy gain, accumulated over 11 consecutive hours. The simulated sequences were generated by means of a dynamic programming algorithm used in conjunction with a food-intake dynamic behavioural model. On one hand, the results obtained do not confirm the hypothesis whereby the animals optimize energy input or output criteria. On the other hand, they do not invalidate the hypothesis according to which the effect of C3H mouse's ultradian activity rhythm would be to maximize net energy gain over a nycthemeral period, possibly under constraints that can only be identified through additional experimentation.

Key words: mouse, ultradian activity, optimization, dynamic programming.

INTRODUCTION

A current dominant paradigm bases every functional analysis of behavioural sequences on optimal decision theory and assumes that present observed successions of acts have been preserved by natural selection because they maximize the fitness of the organisms which perform them (Sibly & McFarland 1976 , Mitchell & Vallone 1990). Such a point of view raises the question of finding what currency organisms maximize, this currency being either directly related to fitness - defined as the total expected lifetime reproductive output (Clark 1991) - or indirectly related to fitness, if the reproductive activity cannot be measured. Energy is often used in behavioural ecology or ethology as a classical currency indirectly related to fitness (Krebs & Davies 1984 , Lendrem 1986).

We propose here a functional analysis of ultradian rest/activity alternations of laboratory mice observed during 11 hr, without any experimental constraints on the various acts the animals are allowed to perform. Besides the lack of functional studies on this specific topic, this analysis is also justifed because laboratory mice and other domesticated or wild rodents have a similar ultradian activity rhythm, that is, a rhythm with a periodicity of less than 24 hr. Indeed, in all these animals, numerous authors have mentioned ultradian rest/activity alternations in addition to a circadian rhythm of preponderantly nocturnal activity (Kavanau 1963 , Del Pozo et al. 1978 , Baumgardner et al. 1980 , Possidente et al. 1980, Aschoff & Gerkema 1985 , Schulz & Lavie 1985 , D'Amato 1986 , Sei et al. 1991 , Bauman 1992 , Gerkema et al. 1993 , Conte et al. 1994). Moreover, according to Beau (1988, 1992), ultradian rhythms of laboratory mice have genetic components. Such behavioural patterns having been preserved by natural selection, it may be asked whether they present a functional value.

In the present work, a currency directly related to fitness cannot be taken into account. Therefore, the energy spent and assimilated is taken as a common currency (McNamara & Houston 1986) for assessing the contributions of the behavioural sequences to three criteria - energy gain, energy cost and net energy gain - which actually constitute classical choices within the framework of the above-mentioned paradigm (Lendrem 1986 fo a review). Such criteria have a strong bearing upon the animal's reproductive and survival potential. They are also compatible with the experimental data available here, as well as with the behavioural model to be described later.

The test of the hypothesis that a given currency is optimized presupposes that one is able to predict how the animal should behave in order to optimize this currency. To do this, one must have

available both a model simulating the succession of rests and activities and an optimization algorithm (Meyer 1980 , Mangel & Clark 1988). This work has involved a dynamic behavioural model which has been used to assign values to the three functional critera for a variety of possible behavioural sequences made up of ultradian rest/activity alternations. In addition, a dynamic programming algorithm effected a selection of the sequences optimizing the three criteria. A comparison among the optimal sequences and the actual sequences has made it possible to assess the coherency of the overall optimization hypothesis of the functional criteria focused upon.

METHOD

This section describes the observation conditions of the actual animals, the functional criteria, and the optimization procedure.

Conditions of the observed behavioural sequences

Twenty C3H males, 4 to 6 weeks old, were isolated on their arrival in the laboratory in a 23 x 8 x 8 cm cage containing water and food ad libitum, together with a cotton ball for nest building. They were lodged in an air-conditioned room set at a temperature of 19 to 21° C and a humidity between 60 and 70%. Ten of these (animals a to j) were placed in LD 12:12 condition, and 10 others (animals A to J) in DL 12:12 condition from 07:00 a.m. to 07:00 p.m. - where L corresponds to the diurnal condition (lighting with fluorescent white 100-lux tubes) and D to the nocturnal condition (lighting with fluorescent red 10-lux tubes, to ensure visibility). Observations began 19 days after receiving the animals: 15 days during which they were kept in the nursery and 4 d ays during which their individual cage were placed in a 52 x 125 x 90 cm observation enclosure.

Chronological sequences of 10 acts (rest, locomotion, feeding, drinking, sniffing, nesting and four categories of grooming) were recorded continuously over an 11-h.r period, during the diurnal period for mice a to j and during the nocturn al period for mice A to J. However, in this present work, only rest (combining rest and a cat egory of grooming that occurs during rest periods), and activity (combining all the remaining acts) alternations are taken into account, rather than a detailed succession of acts. As was shown in another works (Guillot 1988, 1991), C3H mice activity is preponderant at night and prese nts an ultradian rhythm in both day and night. In fact, the animals engage in between four and seven activity periods by day (average duration = 26 min) and from three to four activity periods by night (average duration = 84 min).

Functional optimization criteria

The present analysis centered upon three criteria indirectly related to fitness that were called upon to assess the selective value of the various sequences considered in this work:

The INPUT criterion, representing energy intake, i.e. assimilable energy contained in the food ingested by the animal during its behavioural sequence. At first glance, such a criterion might be maximized by the mouse.

The OUTPUT criterion, corresponding to energy expenditures, i.e. to the total metabolic outgo exhibited by the animal during its behavioural sequence. These expenditures are dependent, among other things, upon the animal's acts, and might be minimized by the mouse.

The NETGAIN criterion, or net energy gain, which expresses the difference between the amounts of energy accrued to (INPUT) and expended by (OUTPUT) the animal during the behavioural sequence considered. This criterion might be expected to be maximized by the animal.

Optimization procedure

Simulated behavioural sequences

The optimization procedure described here was used to identify, among all possible ones, the behavioural sequences that could be compiled from arbitrary alternations of activity and rest periods, those that maximize each of the three criteria considered. These simulated sequences have the same duration as the observed sequences - 11 hr. - and are assembled by successive juxtapositions of 22 elementary activity or rest bouts of 30 min. The duration of these elementary bouts corresponds roughly to the average length of diurnal activity periods as measured on actual animals. In these simulated sequences, several activity - or rest - bouts were allowed to follow each other, so particular simulated activity - or rest - periods were able to last more than 30 min.

Criteria Computation

OUTPUT criterion. In an experiment involving CO_2 releases by mice of the same age, placed in the same conditions as the mice in this study, energy costs were estimated for the activities that could be discerned within the behavioural sequences of these mice (Meyer & Guillot 1986). These estimations, in turn, made it possible to obtain the total energy expenditure resulting from any sequence - observed or simulated - made up of alternating periods of activity and rest. The metabolic cost ascribed to rest was used to calculate the energy expended during simulated rest periods; the average cost of a half-hour of observed activity, computed from all the available observed sequences, was used to calculate the energy expended during simulated activity periods. These values, expressed in Joule per gram per second, are multiplied by the duration in seconds of the corresponding act and by the animal's instantaneous computed weight, then summed from act to act. They yielded the total energy output associated with each behavioural sequence considered.

INPUT criterion. Energy intakes corresponding to simulated sequences were obtained by simulating a variant of the dynamic model of feeding behaviour proposed for the rat by Booth (1978). Essentially, this model links food intake to the instantaneous value of energy flow entering the lean tissues: if this flow falls beneath a given threshold, food intake is triggered; if it exceeds this threshold once again, food intake stops. From a series of metabolic expenditures given as a forcing function, this model correctly predicts the initiation and the termination of the mouse's food intake. It therefore yields the time distribution of the meals and the total quantities of food ingested (Guillot & Meyer 1987 , Guillot 1988).

In brief, this model operates with a 1-sec time step and includes three state variables and nine parameters. The three state variables represent amounts of energy contained in the gut, and in fat and lean tissues. Two of the model's parameters - the gastric clearance and the threshold for the onset and termination of a feeding period - are specific to a diurnal or to a nocturnal situation: in order to simulate a nocturnal situation, the rate of the gastric clearance was increased, and the threshold for the onset and termination of a feeding period was decreased. The other parameters - rate of feeding, food energy density, delay of absorption, maximum of stomach content, three specific coefficients for lipogenesis and lipolysis - were unchanged from one condition to one another.

The energy intake for each observed behavioural sequence could have been computed by multiplying the amount of food actually ingested during the sequence in question by the assimilable energy value of the foodstuff. However, it seemed preferable, for the sake of comparability, to compute these values in the same way they were computed for the simulated sequences, insomuch as the total simulated quantities of food eaten, together with the time distribution of the corresponding feeding bouts, were very similar to the observed results (Guillot & Meyer 1987, Guillot 1988). For this purpose, the following transformation has been effected on the observed sequences in order to render them comparable to the simulated ones.

First, each sequence has been decomposed into 22 successive bouts of 30 min. Second, if the total activity time during each bout did exceed 15 min., the corresponding mouse has been considered as having been active during this bout and, conversely, it has been considered as having been inactive if its total activity time did not exceed 15 min. The patterns, thus transformed into sequences of 0 (= rest) and 1 (= activity), each corresponding to a 30-min. duration, appear in the fifth column of Table 1. Such a transformation - which might be questioned on a priori grounds - did provide two series of 10 observed sequences quite similar from mouse to mouse during day and night conditions (see Fig.1, to be commented later). Then the feeding model was applied to the observed and to the simulated sequences as well, in order to determine the corresponding energy intake.

NETGAIN criterion. The total net energy gain associated with each sequence was computed by subtracting the total energy gain (INPUT) from the total energy expenditures (OUTPUT) of the sequence, computed as stated above.

Optimization algorithm.

The rest/activity alternations likely to optimize, over an 11-hr period, each of the three criteria defined above (INPUT, OUTPUT, and NETGAIN) were derived by means of a dynamic programming algorithm (Guillot 1988, 1991). This algorithm must generate behavioural sequences made up of alternations of activity and rest. It must then provide each one of these sequences as a forcing function to the dynamic model of feeding behaviour in order to compute the corresponding intakes and outgoes. Lastly, it must select the sequences that optimize each of the criteria considered.
The search for the optimal activity and rest alternations by dynamic programming is equivalent to simulating several versions of the feeding model simultaneously. It is however not necessary to simulate as many versions as there are possible combinations of such alternations, because some simulations can be dropped along the way. Indeed, consequently to each of these forcing functions, the feeding model generates a trajectory in the space of the three state variables that characterize it. At any moment between the beginning and the end of the 11-hr. of the simulation, the cumulated value of each of the criteria along the trajectory pursued can be calculated. Accordingly, since the model is deterministic, two trajectories that intersect in the space of the state variables are no longer distinguishable from each other, because they have identi cal future forcing. Therefore, in virtue of the optimality principle - that specifies that every subtrajectory of an optimal trajectory must itself be optimal (Bellman 1957) - when two or more trajectories intersect, only the one having the highest cumulated value of the criterion (in the case of a maximization problem), or the lowest value (in the case of a minimization problem) - from the beginning of the simulation up to the moment of intersection - is the one that may belong to the optimal trajectory. The other trajectories can accordingly be discarded, which simplifies subsequent comparisons that much more.
At the end of the simulation, the last computation loop provides several trajectories: one which corresponds to the highest (maximization) or to the lowest (minimization) value of the criterion and which accordingly represents the absolute optimal trajectory. The other trajectories, which have been kept by the algorithm until this stage, might have been included in the optimal trajectory in case the simulation had last longer. Each of these sub-optimal trajectories can be interpreted as a trajectory that optimizes the criterion at the end of the simulation, provided that an ad-hoc terminal constraint is satisfied - i.e., a constraint that can be specified on a posteriori grounds only and that makes this specific trajectory more advantageous than any other (including the true optimal trajectory) at that specific stage of the simulation. Because each of these trajectories could, additionally, be included in the optimal trajectory correspo nding to a longer simulation, it has been considered interesting to take them into consideration - in the same way as the optimal trajectory, determined at the end of 11 hr of simulation - in the comparisons made below.
The trajectory intersections responsible for simplifying the calculations have been determined to within a few approximations. In the work presented here, the state space was divided into 64

(4^3) equivalency classes, defined by dividing into four equal parts the interval of variation of each of the three state variables of the feeding model. Two or more trajectories were considered to have intersected whenever they felt into the same equivalency class at a given time step. Under these conditions, instead of having to manage simultaneously 2^{22} behavioural sequences, composed of 22 successive bouts of activity or of rest, the dynamic programming algorithm has resulted in managing only 1 to 64 behavioural sequences, according to their relative distributions in the space of the state variables. For the sake of comparability, values associated with the observed sequences have been computed in the same manner as the values associated with the simulated sequences, i.e. with the same parameters of energy expenditure and the same classification procedure among the 64 equivalency classes at each stage of the calculation.

RESULTS

Table 1 shows the diurnal and nocturnal values of the three criteria associated with each of the observed sequences and with each of the optimal sequences. The results obtained indicate that the simulated sequences that maximize INPUT are those where the animals are active all the time - even if they do not eat all the time, as shown in the last column - and that the simulated sequences that minimize OUTPUT are those where the animals are always inactive. As such results could be foreseen, we take them as an indication that the algorithm and the simulations model used here were correctly implemented.

Table 1.

Results associated with approximations of the observed rest (0) and activity (1) alternations, with a 30 min time-step.

A. Day condition
Observed sequences

Mice	Input (J)	Output (J)	Net gain (J)	Observed patterns	Total activity duration (hr., min.)	Total feeding duration (hr., min.)
a	12335.3	14985.6	-2650.3	1110000000010000010011	3.30	0.47
b	13353.6	15892.6	-2539.0	1100011000001000011001	4.00	0.51
c	13702.8	15233.1	-1530.3	1001000100000000100010	2.30	0.52
d	13557.2	15443.9	-1886.7	1100011000010000100011	4.00	0.51
e	13760.9	16779.2	-3018.3	1000010000001100011111	4.30	0.52
f	11831.1	15499.6	-3668.5	1110000110000000000011	3.30	0.45
g	12897.8	14215.9	-1318.1	0001100001000000001001	2.30	0.49
h	13033.6	14602.9	-1569.3	1000001000001000100110	3.00	0.49
i	8286.6	12984.9	-4698.3	1100000000000000011001	2.30	0.31
j	12568.1	15021.0	-2452.9	1100010000000000100111	3.30	0.48

Table 1 (following)
    Optimal sequences

Criteria	Input (J)	Output (J)	Net gain (J)	Optimal sequences	Total activity duration (hr., min.)	Total feeding duration (hr., min.)
NET	13581.5	14816.7	- 1235.2	1000100010001000100010	3.00	0.51
OUTPUT	0.0	**9192.8**	- 9192.8	0000000000000000000000	0.00	0.00
INPUT	18682.4	29723.7	-11041.3	1111111111111111111111	11.00	1.11

B. Night condition
    Observed sequences

Mice	Input (J)	Output (J)	Net gain (J)	**Observed behavioural sequences**	Total activity duration (hr., min.)	Total feeding duration (hr., min.)
A	80010.0	26041.0	53969.0	1111111111001111000111	8.30	5.05
B	78919.0	25091.8	53827.2	1111111111110011000011	8.00	5.01
C	79884.0	26070.3	53813.7	1111111111111100011101	9.00	5.05
D	77866.8	26248.5	51618.3	0111111111111110011001	8.30	4.57
E	81338.6	26718.3	54620.3	1111111110011111111100	9.00	5.10
F	83098.8	28418.7	54680.1	1111111111111111001111	10.00	5.17
G	79617.3	26546.5	53070.8	1111111001111110001111	8.30	5.04
H	81382.2	27530.5	53851.7	1111111111110011011111	9.30	5.10
I	73837.6	25573.6	48264.0	1111111111111000001111	8.30	4.42
J	81513.2	28609.2	52904.0	1111111111111100111111	10.00	5.11

    Optimal sequences

Criteria	Input (J)	Output (J)	Net gain (J)	Optimal sequences	Total activity duration (hr., min.)	Total feeding duration (hr., min.)
NET	83622.3	27551.1	56071.2	1101011011111111111111	9.30	5.19
OUTPUT	0.0	9341.9	-9341.9	0000000000000000000000	0.00	0.00
INPUT	85435.7	30310.8	55124.9	1111111111111111111111	11.00	5.26

Table 2 shows the sequences retained by the dynamic programming algorithm at the last step of the maximization of NETGAIN criterion. These sequences represent both the optimal trajectory

and the sub-optimal trajectories - that can be interpreted as taking into account unspecified terminal constraints, as explained above. The diurnal optimal sequence maximizing NETGAIN is a cyclic pattern of 6 short activity bouts and, at night, the optimal sequence maximizing NETGAIN consists in an irregular pattern of 3 short activity bouts, followed by 1 long one. Such differences between optimal day and night patterns can be ascribed to the causal mechanisms implemented in the feeding model used here. Indeed, in daytime, a high feeding threshold and a low gastric clearance elicit short or rare meals when the animal is active, even for a long time. Then, the net energy gain is higher when the animal spends more time resting instead of activating. In nighttime, a low feeding threshold and a high gastric clearance elicit long or frequent meals when the animal is active. Then, it can spend more energy in being active a long time, because the expenditures are balanced by sufficient energy gain.

The simulated sequences can be compared to the observed sequences, from the standpoint both of rest/activity alternations and of energy intake, energy expenditure, or net energy gain. If rest/activity alternations alone are considered, a purely qualitative comparison of the cumulative activities reveals that it is quite unlikely that, in day condition (Fig.2A), mice maximize their total energy intake, as the optimal sequences differ widely from the observed ones. Likewise, it would not seem that the animals minimize, in day and night conditions, their total energy expenditure. On the contrary, the patterns that maximize the total net energy gain do bear a resemblance to the observed patterns in both day and night conditions (Fig.2 A - B).

Table 2.

Detail of the results associated with the optimal (O) and sub-optimal (S) sequences maximizing NET. Theoretical sequences are decrementally sorted by their net gain values.

A. Day condition

Input (J)	Output (J)	Net gain (J)		Theoretical sequences	Total activity duration (hr., min.)
13581.5	14816.7	-1235.2	O	1000100010001000100010	3.00
13576.7	14816.6	-1239.9	S	1000100010001000100001	3.00
14362.1	15746.9	-1384.8	S	1000100010001000100011	3.30
13140.2	14819.5	-1679.3	S	100100010001000100	3.00
13920.9	15749.3	-1828.4	S	100100010001000110	3.30
14711.3	16680.2	-1968.9	S	100100010001001101	4.00
14687.0	16678.5	-1991.5	S	100100010001000111	4.00
12689.3	14820.2	-2130.9	S	100100010001001000	3.00
13470.0	15750.0	-2280.0	S	100100010001001100	3.30
13426.3	15744.7	-2318.4	S	1000100010001000011010	3.30
14236.0	16678.5	-2442.5	S	100100010001001110	4.00
14192.4	16673.7	-2481.3	S	1000100010001000011011	4.00
14187.6	16672.8	-2485.2	S	1000100010001000111010	4.00
14173.1	16672.0	-2498.9	S	1000100010001000011101	4.00
12956.0	15744.3	-2788.3	S	1000100010001000111000	3.30
12946.3	15743.0	-2796.7	S	1000100010001000011100	3.30
13445.7	17605.6	-4159.9	S	0110001011000110001100	4.30
13440.9	17605.0	-4164.1	S	0110001011000110000110	4.30
12194.7	16674.1	-4479.4	S	0110001100011000110000	4.00

Table 2 (following)

B. Night condition

Input (J)	Output (J)	Net gain (J)		Theoretical sequences	Total activity duration (hr., min.)
83622.3	27551.1	56071.2	O	11010110111111111111111	9.30
83505.9	27543.0	55962.9	S	11010101111111111111111	9.30
84296.3	28476.9	55819.4	S	11010111111111111111111	10.00
83215.0	27540.2	55674.8	S	11001011111111111111111	9.30
83030.8	27512.8	55518.0	S	11011100111111111111111	9.30
84883.0	29396.0	55487.0	S	11011111111111111111111	10.30
85435.7	30310.8	55124.9	S	11111111111111111111111	11.00
80048.7	26583.1	53465.6	S	11010110111111111111110	9.00
79495.9	26546.7	52949.2	S	11011100111111111111110	9.00
81362.8	28430.8	52932.0	S	11011111111111111111110	10.00
81939.8	29347.0	52592.8	S	11111111111111111111110	10.30
78448.6	28384.8	50063.8	S	11111111111111111111100	10.00
76480.0	25616.2	50863.8	S	11010110111111111111100	8.30
75961.2	25582.4	50378.8	S	11011100111111111111100	8.30
77847.4	27467.3	50380.1	S	11011111111111111111100	9.30
72911.3	24650.3	48261.0	S	11010110111111111111000	8.00
74332.0	26504.8	47827.2	S	11011111111111111111000	9.00
72431.3	24619.1	47812.2	S	11011100111111111111000	8.00
74957.5	27423.7	47533.8	S	11111111111111111111000	9.30
8727.8	10285.9	-1558.1	S	10000000000000000000000	0.30

To extend this comparison to the quantitative criteria ava ilable, a clustering algorithm, opera-
ting by nearest centroid sorting (Anderberg 1973), has been applied to the actual and the theoretical
sequences associated with each criterion. These classifications are operated on the basis of either
INPUT, OUTPUT, or NETGAIN values that characterize each sequence and are given in Table 3
and Table 4. It will be noted that the observed sequences are sorted in the same cluster as the opti-
mal one maximizing NET, or in the most similar cluster. The actual sequences are not as frequently
sorted with the simulated sequences optimizing OUTPUT or INPUT, and always display higher net
gain values.

Despite such similarities between optimal and actual patterns, it appears that the correspon-
ding matching is not perfect, considering the details of the number and distribution of activity bouts.
In fact, the characteristics of observed mice patterns correspond, in day condition (Table 1A), to
less activity bouts with irregular patter ns - instead of regular ones - and, in night condition (Table
1B), to a long activity bout at the beg inning of the period - instead of at the end. This is exemplified
in Fig.3 , that shows the actual activity patterns of 2 mice together with the simulated patterns opti-
mizing NETGAIN.

Table 3.

Cluster summaries for day condition. The optimal (O) and sub-optimal (S) sequences, together with the 10 observed sequences (a-j), have been clustered by nearest centroid sorting.

A. INPUT OPTIMIZATION

Cluster	Nearest cluster	Average input (J)	Average output (J)	Average net gain (J)	Theoretical sequences	Observed sequences
1	4	17664.2	27869.3	-10205.1	O,S,S,S,S,S,S,S	
2	3	14848.6	19797.5	- 4948.9	S,S,S	
3	2	12532.7	15065.9	- 2533.2		a,b,c,d,e,f,g,h,i,j
4	1	16904.8	25435.5	- 8530.7	S,S,S,S,S,S,S,S	

B. OUTPUT OPTIMIZATION

Cluster	Nearest cluster	Average input (J)	Average output (J)	Average net gain (J)	Theoretical sequences	Observed sequences
1	4	13297.8	14873.9	-1576.1		c,d,g,h
2	3	4922.4	12500.3	-7577.9	S,S,S,S,S,S,S,S,S,S	i
3	2	2419.6	10540.4	-8120.8	O,S,S,S,S,S,S,S,S	f
4	1	12769.8	15635.6	-2865.8		a,b,e,j

C. NET OPTIMIZATION

Cluster	Nearest cluster	Average input (J)	Average output (J)	Average net gain (J)	Theoretical sequences	Observed sequences
1	4	13222.2	14956.6	-1734.4	O,S,S,S,S	a,c,d,g,h,j
2	1	8286.6	12984.9	-4698.3		i
3	4	13027.1	17295.0	-4267.9	S,S,S	
4	1	13703.8	16211.4	-2507.6	S,S,S,S,S,S,S,S,S,S,S	b,e,f

Table 4.

Cluster summaries for night condition. The optimal (O) and sub-optimal (S) sequences, together with the 10 observed sequences (A-J), have been clustered by nearest centroid sorting.

A. INPUT OPTIMIZATION

Cluster	Nearest cluster	Average input (J)	Average output (J)	Average net gain (J)	Theoretical sequences	Observed sequences
1	3	8727.9	10286.0	- 1558.1	S	
2	4	80544.7	26475.0	54069.7	S,S	A,B,C,D,E,G
3	2	75804.0	26827.3	48976.7	S,S,S,S,S,S,S,S	I
4	2	82935.5	28694.9	54240.6	O,S,S,S,S,S,S,S,S	F,H,J

B. OUTPUT OPTIMIZATION

Cluster	Nearest cluster	Average input (J)	Average output (J)	Average net gain (J)	Theoretical sequences	Observed sequences
1	2	0.0	9341.9	- 9341.9	O	
2	3	13203.0	10824.3	2378.7	S,S,S,S,S,S,S,S,S,S,S,S,S	
3	2	26020.6	12419.8	13600.8	S,S,S,S,S	
4	3	80062.1	26762.6	53299.5	S	A,B,C,D,E,F,G,H,I

C. NET OPTIMIZATION

Cluster	Nearest cluster	Average input (J)	Average output (J)	Average net gain (J)	Theoretical sequences	Observed sequences
1	3	8727.9	10286.0	- 1558.1	S	
2	4	80918.2	26732.6	54185.6	O,S,S,S,S,S	A,B,C,D,E,G,H
3	2	75245.3	26202.5	49042.8	S,S,S,S,S,S,S,S	I
4	2	83218.5	28998.5	54220.0	S,S,S,S,S	F,J

DISCUSSION

The results presented herein suggest that, over day and night conditions, ultradian rest/activity alternations could maximize NETGAIN, instead of optimizing either INPUT or OUTPUT criteria. Such conclusions are in line with those of earlier works that suggest that the patterns of particular acts - like feeding and drinking in rats - might be ascribed to energy optimizing processes (Collier & Rovee-Collier 1980, Kagel et al. 1980, Jensen et al. 1983, Ljungberg & Enquist 1986, Johnson & Collier 1989, 1994). It has nevertheless been noted that the observed sequences do not match exactly the optimal ones. The corresponding differences can be explained by both biological and methodological arguments.

Biological arguments.

First, mice might maximize another criterion than the one investigated. In this case, other investigations must be made to specify such a criterion. However, a close correlation between

NETGAIN and this other criterion can be anticipated and would explain the similarities highlighted in the present work between optimal and observed behavioural sequences.

Second, mice might optimize the NETGAIN criterion, but under secondary constraints. For example, most of the mice (A B C D E G H, a c d g h j) tend to maximize NETGAIN while decreasing both their inputs and outputs, and mice F J H tend to maximize NETGAIN while increasing their inputs (Table 3 and Table 4). These differences from optimal patterns, which reflect a modification of excursion patterns outside the nest happening to be differently distributed along the day/night cycle, can be linked with individual differences in rearing conditions, in initial states at the beginning of the observation and in effects of learning. They can also be linked with individual reactivity to constraints of ecological nature, such as a lower risk of predation or the presence of a place the animal can hide in (Nicolaidis et al . 1979 , Ludwig & Rowe 1990). It should also be borne in mind that mice were kept and observed here in isolation, although they normally live in groups. Therefore, social constraints should be involved in the differences described above (Del Pozo et al. 1978, Smith et al. 1994).

Finally, mice might optimize the NETGAIN criterion over a period shorter or longer than 11 hr. Indeed, the present research has focused on such a period for purely technical and methodological reasons. However, it should be noted that the optimization of NETGAIN over a shorter period than 11 hr. would not necessarily have generated an optimal sequence similar to the optimal or sub-optimal 11-hr. sequences given in Table 2. This is due to the fact that a pattern found to be optimal by the dynamic programming algorithm at a given iteration loop can be eliminated later on because it competes with another pattern, which gives better results over a longer time span. On the contrary, an optimization of NETGAIN over a period longer than 11 hr. would necessarily have generated an optimal sequence built upon one of the optimal or sub-optimal 11-hr. sequences and, thus, very similar to these sequences. Their resemblance with actual patterns tends to suggest that mice, optimizing NETGAIN over 12 hr. in day and 12 hr. in night conditions, actually optimize NETGAIN over a nycthemeral period, as already mentioned by Bauman (1992) or Johnson & Collier (1994) for rats.

Methodological arguments

Because the dynamic programming algorithm is particularly greedy in memory capacity, it has not been possible to use it to determine, second by second, the precise optimal act that would have been selected among the ten retained. Such calculations would have allowed an accurate and point-by-point comparison between simulated and observed results. The simulated sequences have been reduced here to alternations of 22 rest/activity bouts of 30 min., and the observed sequences have also been reduced to these approximations. The comparisons between optimal and observed sequences that we have been able to make here are therefore approximate - although they yield to coherent results when, for instance, they specify that the way to maximize INPUT is to be always active and the way to minimize OUTPUT is to be always inactive.

It must also be borne in mind that the different results mentioned here are closely involved with the use of the feeding model and that it should, a priori, be possible that they reflect, not actual biological fact, but rather the operational modes of the model. It can nonetheless be considered that the validations of this model, both in rats (Booth 1978, Clifton et al. 1984) and in mice (Guillot 1988, Guillot & Meyer 1987) make a convincing case for the conclusions presented here. In addition, such a model represents a useful tool for attempting to relate proximate causal mechanisms to ultimate functional factors (Curio 1994).

CONCLUSION

Despite the limitations discussed above, the present functional study can provide hypotheses as to the selection of activity or rest bouts by a laboratory strain of mice. The results obtained suggest that the activity/rest alternations engaged in by the animals tend to maximize their total net energy gain, rather than to maximize their total energy input or to minimize their total energy output over 11 hr. A variety of complementary experiments, notably involving a modification of the energy costs entailed by specific acts exhibited by the mouse (Kanarek & Collier 1979, Johnson & Collier 1994), could be designed for the purpose of confirming the nature of the criterion that tends to be optimized and of identifying the corresponding constraints. However, if this hypothesis is accepted, two prospects can be considered.

The first implies studying how each of the acts carried out by the animal in the course of the activity periods contributes to optimization of the criterion NETGAIN . For this purpose, a comparison of the value of the criterion associated with the actual behavioural succession and the values of the criterion associated with behavioural reorganizations of the same succession has been undertaken (Guillot & Meyer, in press).

The second concerns the way in which the mouse makes its behavioural choices. It is in fact highly improbable that the mouse performs optimization calculations at each time step, as the algorithm used here does, and it seems more reasonable to think that it is guided solely by its sensory inputs, in deciding whether or not it is more advantageous to activate at the next time step (Roughgarden 1991). This is why a neuroethological approach (Beer 1990, Meyer & Guillot 1991, 1994) is under consideration in order to study what mechanisms might be involved in this process. The objective would be to ascertain what nervous architectures might account for decision-making concerning ultradian rest/activity alternations by calling solely on the sensory information known to be accessible to the animal. These architectures might be discovered by means of an evolving process, like genetic programming (Koza 1992), that is inspired from mechanisms responsible for the evolution of species. Such an approach would be complementary to the one used there, for, as Miller & Todd (1991) remark, *"dynamic programming represents an attem pt to understand the results of evolution without simulating evolution"*.

REFERENCES

ANDERBERG M.R. 1973. Cluster analysis for applications. *New-York: Academic Press*.

ASCHOFF J. & GERKEMA M. P. 1985. On the diversity and uniformity of ultradian rhythms. In: Schulz H. & Lavie P., Edits . Ultradian rhythms in physiology and behaviour. *Berlin: Springer-Verlag*.

BAUMAN R.A. 1992. The effects of wheel running, a light/dark cycle, and the instrumental cost of food on the intake of food in a closed economy. *Physiology & Behavior* 52: 1077-1083.

BAUMGARDNER D.J., WARD S.E. & DEWSBURY D.A. 1980. Diurnal patterning of eight activities in 14 species of muroid rodents. *Animal Learning and Behavior* 812: 322-330.

BEAU J. 1988. Mise en évidence de corrélats polygéniques des caractéristiques du rythme de l'activité chez un mammifère: étude de deux lignées de souris consanguines C57BL/6By et BALB/cBY. *Compte-Rendus de l'Acad\émie des Sciences,* Paris (III) 307: 37-40.

BEAU J. 1992. Activity rhythms in mice III: Stability and plasticity of rhythm characteristics in experimental and environmental conditions. *Physiology and Behavior* 52:231-235.

BEER R.D. 1990. Intelligence as adaptive behaviour: an experiment in computational neuroethology. *San Diego: Academic Press*.

BELLMAN R. 1957. Dynamic Programming. *Princeton: Princeton University Press*.

BOOTH D.A. 1978. Prediction of feeding behaviour from energy flows in the rat. In Booth D.A., Edit. Hunger models: computable theory of feeding control. *London: Academic Press.*

CLARK C.W. 1991. Modeling behavioural adaptations. *Behavioral and Brain Sciences* 14 :85-117.

CLIFTON P.G., POPPLEWELL D.A. & BURTON M.J. 1984. Feeding rate and meal patterns in the laboratory rat. *Physiology and Behavior* 32: 369-374.

COLLIER G.H. & ROVEE-COLLIER C.K. 1980 . A comparative analysis of optimal foraging behaviour: laboratory simulations. In Kamil A.C. & Sargent T.D., Edits. Foraging behaviour: ecological, ethological and physiological approaches. *New-York: Garland Press*

CONTE S., D'OLIMPIO F., FERLAZZO F., MAZZUCHELLI A. & RENZI P. 1994. Ultradian rhythms in avoidance behaviour of DBA mice. *Physiology and Behavior* 55: 287-292.

CURIO E. 1994. Causal and functional questions: how are they linked? *Animal Behaviour* 47: 999-1021.

D'AMATO F.R. 1986. Time budgets and behavioural synchronization in aggregated and isolated male and female mice. *Behavioural Processes* 13: 385-397.

DEL POZO F., DeFEUDIS F.V. & JIMENEZ J.M. 1978. Motilities of isolated and aggregated mice: a difference in ultradian rhythmicity. *Experientia* 10: 1302-1304.

GERKEMA M.P., DAAN S., WILBRINK M., HOP M.W. & VAN DER LEEST F. 1993. Phase control of ultradian feeding rhythms in the common vole, Microtus arvalis : the roles of light and the circadian system. *Journal of Biological Rhythms* 2: 151-171.

GUILLOT A. 1988. Contribution à l'étude des séquences comportementales de la souris: approches descriptive, causale et fonctionnelle. *Diplôme de Doctorat de l'Université Paris 7. Spécialité Biomathématiques.*

GUILLOT A. 1991. Le comportement de la souris *Mus computatrix. Habilitation à diriger des recherches en Psychophysiologie. Université Paris X.*

GUILLOT A. & MEYER J.A. 1987. A test of the Booth energy flow model (Mark 3) on feeding patterns of mice. *Appetite* 8: 67-78.

GUILLOT A. & MEYER J.A. (in press). A cost/benefit analysis of behavioural sequences in mice.

JENSEN G.B., COLLIER G.H. & MEDVIN M.B. 1983. A cost benefit analysis of nocturnal feeding in the rat. *Physiology and Behavior* 31: 555-559.

JOHNSON D.F. & COLLIER G. H. 1989. Patch choice and meal size of foraging rats as a function of the profitability of the food. *Animal Behaviour* 38: 285-297.

JOHNSON D.F. & COLLIER G. H. 1994. Meal patterns of rats encountering variable food procurement cost. *Animal Behaviour* 47: 1279-1287.

KAGEL J.H., BATTALIO R.C., GREEN L. & RACHLIN H. 1980. Consumer demand theory applied to choice behaviour of rats. In Staddon J.E., Edit. Limits to action. The allocation of individual behaviour. *London: Academic Press*

KANAREK R.B. & COLLIER G.H. 1979. Patterns of eating as a function of the cost of the meal. *Physiology and Behavior* 23: 141-145.

KAVANAU J.L. 1963. Continuous automatic monitoring of the activities of small captive animals. *Ecology* 44: 95-110.

KOZA J.R. 1992. Genetic programming: on the programing of computers by means of natural selection. *Cambridge: The MIT Press.*

KREBS J.R. & DAVIES N.B., Edits. 1984. Behavioural ecology: an evolutionary approach. *Oxford: Blackwell.*

LENDREM D. 1986. Modelling in behavioural ecology: an introductory text. *Portland: Timber Press* .

LJUNGBERG T. & ENQUIST M. 1986. Decision making by rats in an unpredictable laboratory environment: final decision rules. *Animal Behaviour* 34: 1120-1128.

LUDWIG D. & ROWE L. 1990. Life-history strategies for energy gain and predator avoidance under time constraints. *The American Naturalist* 135, 5: 686-705.

McNAMARA J.M. & HOUSTON A.I. 1986. The common currency for behavioural decisions. *American Naturalist* 127: 358-378.

MANGEL M. & CLARK C.W. 1988. Dynamic modeling in behavioural ecology. *Princeton : Princeton University Press.*

MEYER J.A. 1980. Techniques d'étude des stratégies adaptatives: approches mathématiques et informatiques. In Barbault R. et al., Edits. Recherches d'écologie théorique. Les stratégies adaptatives. *Paris: Maloine.*

MEYER J.A. & GUILLOT A. 1986. The energetic cost of various behaviours in the laboratory mouse. *Comparative Biochemistry and Physiology* 83, 3: 533-538.

MEYER J.A. & GUILLOT A. 1991. Simulation of adaptive behaviour in animats: review and prospect. In Meyer J.A. & Wilson S.W., Edits. From animals to animats. Proceedings of the First International Conference on Simulation of Adaptive Behavior. *Cambridge: The MIT Press/Bradford Books.*

MEYER J.A. & GUILLOT A. 1994. From SAB90 to SAB94: four years of animat research. In Cliff D., Husbands P., Meyer J.A. & Wilson S.W., Edits. From animals to animats 3.

Proceedings of the Third International Conference on Simulation of Adaptive Behavior. Cambridge: *The MIT Press/Bradford Books.*

MILLER G.F. & TODD P.M. 1991. Let evolution take care of its own. Open peer commentary for Clark (1991): Modeling behavioural adaptations. *Behavioral and Brain Sciences* 14 : 101-102.

MITCHELL W.A. & VALLONE T.J. 1990. The optimization research program: studying adaptations by their function. *Quarterly review of Biology* 0 65: 43-52.

NICOLAIDIS S. , DANGUIR J. & MATHER P. 1979. A new approach to sleep and feeding behaviours in the laboratory rat. *Physiology and Behavior* 23: 717-722.

POSSIDENTE B, HEGMAN J.P., HELDER B. & CARLSON L. 1980. Dissociation of circadian rhythms for food and water consumption in mice. *Physiology and Behavior* 25: 279-281.

ROUGHGARDEN J. 1991. Rule of thumb. Open peer commentary for Clark (1991): Mo deling behavioural adaptations. *Behavioral and Brain Sciences* 14 : 104-105.

SEI H., AZEKAWA T. & MORITA Y. 1991. Ultradian rhythm of 100 min in the dark phase EEG of the rat. *Physiology and Behavior* 49: 207-210.

SCHULTZ H. & LAVIE P. , Edits. 1985. Ultradian rhythms in physiology and behavior. *Berlin: Springer Verlag.*

SIBLY R.M. & McFARLAND D.J. 1976. On the fitness of behaviour sequences. *American Naturalist* 110: 610-617.

SMITH J., HURST J.L . & BARNARD C.J . 1994. Comparing behaviour in wild and laboratory strains of the house mouse: levels of comparison and functional inference. *Behavioural Processes* 32: 79-86.

FIGURE CAPTIONS

Fig. 1. Cumulative activity of observed behavioural sequences translated into rest/activity alternations with a 30-min. time step and of optimal sequences generated by dynamic programming.
A, Day condition
B, Night condition.

Fig. 2. Optimal and actual patterns.
A, Theoretical alternations optimizing NET criterion
B, Observed alternations having the same total activity duration than the optimal ones (mouse h in day condition and mouse H in night condition).