Modelling Sleep Stages With Markov Chains

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1 Introduction

Sleep research is a relatively young discipline. Before the 20th century, there were no practical methods to study sleep besides the analysis of dreams. From 1920s onwards, the invention of electroencephalography (EEG) and other advances have made it possible to better understand the electrical activity of the brain. The discovery of rapid eye movement (REM) sleep established the fact that sleep is divided into phases with different characteristics and functions. Describing and explaining them remains a major research challenge. [1]

From a clinical point of view, sleep-related pathologies are difficult to study and cure. Long measurements in specialised laboratories are often needed for the analysis of sleep. This can be expensive and taxing for patients and clinicians alike. Despite the difficulties, sleep medicine has advanced and developed treatments to pathologies like sleep apnea and narcolepsy. Effects of more general disturbances in sleep have also been a subject of interest. They are common and affect a significant part of the population. [1]

Sleep as a biological phenomenon is closely related with the electrical activity of the brain. Recordings of EEG, EOG (electro-oculography) and EMG (electromyography) form time series. However, recording a patient’s EEG, EOG and EMG for even a single night of sleep produces a large quantity of data. Therefore it is customary to classify sleep recordings into stages. This is possible because of the regularities in the structure of sleep. Statistical analysis can then be performed on the staged data. [2], [3]

Traditionally, stage scoring has been done by visually analyzing EEG, EOG and EMG recordings. This method requires an experienced sleep technician to perform the staging. To save resources and increase accuracy, automatic staging procedures have been developed. Among them are technical solutions based on, for example, pattern matching, and neural networks [4]. At the present moment, the traditional visual method remains the standard. Automatic procedures can be useful additional tools for visual scoring, but their performance as a standalone method is not satisfactory [5].

There are various ways to use the scored sleep stage data. The basic idea is to recognize structures in sleep and then link them with relevant physiological phenomena. For example, patients with narcolepsy usually proceed to REM sleep straight from wakefulness instead of going through other sleep stages.
Also, correctly assessing the severity of sleep apnea benefits from sleep staging. How then to describe the structure of sleep based on stage data? The sum of stage counts during a relevant period of time (for example, the whole or one third of the night) is the simplest statistic used. Visual analysis is made possible by the use of hypnograms, which are graphs of sleep stage data plotted against time. [1]

Another way to use sleep stage data is the construction of Markov models. A simple time-homogenous Markov chain was the first attempt to use this approach [6]. Later on, semi-Markov chains [7] and time-continuous Markov models [8] have been developed. Creating simulated hypnograms with Monte Carlo methods is a major application for this type of models. For example, effects of aircraft noise on sleep structure can be studied. Literature reports that Markov models have been used for simulating sleep under different conditions or scenarios. With simulated stage recordings, hypnograms and sleep parameters can be compared between conditions [9].

In this study, empirical data is analyzed for two purposes. Firstly, the following hypothesis is tested: if a person has slept less than normally, the amount of Slow Wave Sleep (SWS) increases. This is a widely reported phenomenon in the literature [10], [1]. For example, if there is a one night when the subject cannot sleep normally, the next night there is probably going to be more SWS in her sleep. This study compares the possible statistical difference of the amount of SWS epochs between the Normal and Recovery nights. The hypothesis is that this approach should yield the standard literature result of increased SWS during recovery nights.

Secondly, a Markov chain probability matrix is used to find out, how the transitions from one stage to another are distributed. Estimating a transition matrix from a sample of multiple nights offers a description of the sleep’s structure under given conditions. Furthermore, statistical comparisons of these matrices tell how different conditions affect the transitions between stages.

This study has five main parts. Section 2 describes some basic information about sleep stages. In Section 3 a simple Markov model is presented for analysing sleep stage data. Also, relevant theoretical aspects are reviewed. Methods of the study are described in Section 4 and the results are presented in Section 5. The results are discussed in Section 6 where some suggestions for the course of future research are made. Also, the adequacy of the used Markov model and other questions of validity are assessed.
Sleep can be defined theoretically as "reversible behavioral state of perceptual disengagement from and unresponsiveness to the environment" [1]. At the level of common sense, we all know what sleep is, but its physiology is an amalgam of complex phenomena. On average young people usually sleep 7.5 hours during weeks and 8.5 hours during weekend nights. However, this and many other aspects of sleep vary, so it is difficult to describe "normal" sleep [1].

There are three main physiological signals used for sleep staging (scoring).

**Table 1:** Time spent in different sleep stages

<table>
<thead>
<tr>
<th></th>
<th>W</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>SREM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0-5%</td>
<td>2-5%</td>
<td>45-55%</td>
<td>3-8%</td>
<td>10-15%</td>
<td>20-25%</td>
</tr>
</tbody>
</table>

**Figure 1:** Hypnogram of a Normal night’s sleep. (Horizontal axis is 30 second epochs from lights off)
Figure 2: Hypnogram of a Recovery night’s sleep. (Horizontal axis is 30 second epochs from lights off)
These techniques are electroencephalography (EEG), electro-oculography (EOG) and electromyography (EMG). EEG measures brain activity with electrodes placed on the scalp. EOG measurements record the movement of eyes. EMG tells about the physiological properties of muscles, in this case their tension. Together with these three techniques it is possible to find out in which sleep stage the subject is. [3], [2]

Sleep can be divided into three main different phases: wake, non-rapid eye movement (NREM) sleep and rapid eye movement (REM) sleep. In analysis, sleep stages are used as subcategories of these phases. Wake is considered a stage (denoted W) in itself. NREM sleep is associated with a low level of mental activity. It consists of four stages: S1, S2, S3 and S4. The intensity of sleep is roughly weakest at S1 and strongest at S4. Light sleep is typical of the type S1 or S2, deep sleep of S3 or S4. The number and definition of stages varies in the literature. For example, S3 and S4 are sometimes combined into Slow Wave Sleep (SWS) [3]. This is the convention adopted in this study. On the other hand, SREM (Stage REM) is defined as a stage of sleep with rapid eye movements (REM). It is thus a subcategory of REM sleep. Sleep stages are usually scored visually in 30 (or 20) second epochs. Ensuing discrete data series can then be analyzed. Technicians doing the scoring have to be experienced because the process depends on their judgement and ability. [1], [11]

Hypnograms are plots that tell about the distribution and time evolution of sleep stages. They are plots of recorded data that show visually how the sleep of the subject is structured. Many clinical applications of hypnograms have been developed. For a clinician, an easy rule of thumb based on analysis of hypnograms can be valuable. [1]

Figures 1 and 2 show examples of hypnograms. Both are based on one-night recordings. Figure 1 describes sleep under the Normal condition. In Figure 2, the same subject has experienced loss of sleep and is now recovering during the following night. The time scale of the these hypnograms is 960 epochs of 30 seconds, which amounts to a total of 8 hours of sleep. Varying conditions like the amount of sleep in the previous nights and stress affect the structure of sleep, which can be seen in the hypnograms. Of course, the subjects’ personal attributes are also important and no two hypnograms are exactly alike.

In normal human sleep, there are cycles in which REM and NREM alternate. As the night goes on, REM episodes tend to get longer. Typical distribution
of stages is presented in Table 1 (adapted from [1]).

3 Markov Chain Model

The idea that transitions between sleep stages can be modelled as a Markov process is not new. Currently, advanced models are based on continuous-time Markov chains [8], [9]. In this study we limit to a time-homogenous Markov chain, along the lines of Zung et al.’s pioneering work [6]. Whether this model is detailed enough, is a serious issue. However, it has to be kept in mind that the main objective of this study is to compare stage transitions between the two conditions.

This section presents basics of Markov chains and how they can be applied to modeling sleep stages. A simple model of human sleep is developed alongside the more theoretical material. The section is based on Taylor and Carlin’s book [12].

We define a discrete time Markov chain \( \{X_t\} \) as a stochastic process satisfying the following conditions:

1. The state space \( S \) is a finite or countable set.
2. The time index set is \( T = (0, 1, 2, \ldots) \)
3. The chain has the Markov property, i.e. the conditional probability distribution of all the possible changes in the system’s state is not affected by knowledge of its history besides the current state.

The Markov property can be formalized as:

\[
\Pr\{X_{n+1} = j | X_0 = i_0, \ldots, X_{n-1} = i_{n-1}, X_n = i\} = \Pr\{X_{n+1} = j | X_n = i\}
\]

for all \( n \in T \) and all states \( i_0, \ldots, i_{n-1}, i, j \).

How does the human sleep as a process meet these criteria? We saw in the
previous section that sleep can be classified into five discrete stages: W, SREM, S1, S2 and SWS. Thus it is natural to choose them as the states of the process, yielding \( S = \{W, \text{SREM}, \text{S1}, \text{S2}, \text{SWS}\} \). As stage information is a discrete time series, there is no problem constructing the time index set \( T \). The Markov property and time-homogenous nature of the probability distribution hold at least approximately, although actual empirical data shows some non-stationary properties \([6], [8], [9]\).

Transition probabilities of the chain \( \{X_t\} \) can be arranged in a \( n \times m \) matrix:

\[
P = \begin{bmatrix}
p_{11} & p_{12} & \cdots & p_{1m} \\
p_{21} & p_{22} & \cdots & p_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
p_{n1} & p_{n2} & \cdots & p_{nm}
\end{bmatrix}
\]

The probability of going from the state \( i \) to \( j \) in one step is \( p_{ij} \).

In this study, the following transition matrix is used:

\[
P = \begin{bmatrix}
p_{W\rightarrow W} & p_{W\rightarrow \text{SREM}} & p_{W\rightarrow \text{S1}} & p_{W\rightarrow \text{S2}} & p_{W\rightarrow \text{SWS}} \\
p_{\text{SREM}\rightarrow W} & p_{\text{SREM}\rightarrow \text{SREM}} & p_{\text{SREM}\rightarrow \text{S1}} & p_{\text{SREM}\rightarrow \text{S2}} & p_{\text{SREM}\rightarrow \text{SWS}} \\
p_{\text{S1}\rightarrow W} & p_{\text{S1}\rightarrow \text{SREM}} & p_{\text{S1}\rightarrow \text{S1}} & p_{\text{S1}\rightarrow \text{S2}} & p_{\text{S1}\rightarrow \text{SWS}} \\
p_{\text{S2}\rightarrow W} & p_{\text{S2}\rightarrow \text{SREM}} & p_{\text{S2}\rightarrow \text{S1}} & p_{\text{S2}\rightarrow \text{S2}} & p_{\text{S2}\rightarrow \text{SWS}} \\
p_{\text{SWS}\rightarrow W} & p_{\text{SWS}\rightarrow \text{SREM}} & p_{\text{SWS}\rightarrow \text{S1}} & p_{\text{SWS}\rightarrow \text{S2}} & p_{\text{SWS}\rightarrow \text{SWS}}
\end{bmatrix}
\]

For example, the elements of the second row represents the probabilities of transitions from SREM state to state \( x \in S = \{W, \text{SREM}, \text{S1}, \text{S2}, \text{SWS}\} \). Note that changes from a stage to itself (SREM\(\rightarrow\)SREM etc.) are also considered transitions.

Figure 3 offers visualization of a simple Markov chain. Here, the probability of going from state 2 to state 3 in one step is 0.4. The total probability of transitions from a single state is one. In the figure, impossible transitions, i.e. those having a zero probability, are not indicated. Notice that once the process enters state 1, it stays there indefinitely.

Next we consider the behavior of the process over multiple steps. For example, if the process starts at stage W, what is the probability that it will be at SREM after 9 steps (\( n = 9 \))? We note the probability of transition from state \( i \) to \( j \) in \( n \) steps with \( p_{ij}^{(n)} \). The matrix \( P^{(n)} \) includes all transition
probabilities for a given value of $n$. It can be shown (see for example [12]) that the $n$-step transition probabilities $p_{ij}^{(n)}$ are entries of $n$th power of the matrix $P$. From this we conclude that $P^{(n)} = P^n$.

The transition probability matrix $P$ is a parameter of the Markov model. It can be estimated with the relative frequency of the number of transitions. For example, if there are 6 $W \rightarrow$ SREM transitions and a total number of 30 transitions from $W$ in a dataset, then $p_{W \rightarrow SREM}$ is 0.2. By increasing the sample size, the estimation can be made more accurate because of the law of large numbers. Note that in this study, the used datasets can be either recordings of one night’s sleep or aggregates over multiple nights. When it comes to estimating the probability matrices, this does not change the procedure.

4 Methods

In the dataset, there are 21 normal male adult subjects with an age range of 18-22 (mean 21). The study design has been reported earlier by Sallinen et al.
The subjects’ sleep was studied during five nights. The first night was to screen for sleep disorders which would have disqualified subjects from the study. Two nights were normal nights. The latter of those was used here. Then, a night with only two hours for was sleeping followed by a Recovery night.

In this study, the nights used form the data mentioned above are the Normal night and the Recovery night. The equipment used was digital Embla N7000 (EMBLA, Broomfield, CO, USA). One experienced sleep technician scored the recordings visually. The standards used were normal EEG, EOG, and EMG montage [3].

A wide consensus exists in the literature that there should be more Slow Wave Sleep (SWS) under Recovery conditions [13]. This study has two research questions. Firstly, can the SWS-hypothesis be verified by comparing the epoch counts under the two conditions? For this, the data is categorized by subject and a paired Wilcoxon test is performed to see the differences between the Normal and Recovery conditions. The second question is, how do the same conditions affect the transitions? There is no clear hypothesis available so this part of the study is explorative in nature. The change of stages over time is modelled as a Markov chain. Transition probabilities are estimated by calculating the relative frequencies of transitions with a customized Delphi-based software created by the author. A paired Wilcoxon test is then conducted on the estimated transition matrices. The reported p-values are uncorrected. Statistical tests are performed with R [14].

5 Results

The first result of the data analysis is the distribution of epochs categorized by subject and condition. Note that the count of epochs for any stage is equivalent to the number of transitions from (or to) that stage. After each epoch spent in a stage there occurs a transition. This follows from the logic of the Markov chain model presented in the Section 3.

Graphs of the stage count data (Figure 4) show that the conditions seem to have a systematic effect on the stage counts. The variation between subjects was most emphasised in the W stage (Figure 4a).

Table 2 presents a summary of the epoch count data under the two conditions.
Both Normal and Recovery conditions are listed. For example, the standard deviation of the number of S2 epochs was 69 (Normal) and 72 (Recovery). The variation between data points was probably caused by subjects’ personal traits, the effect of conditions, and measurement errors.
Table 2: Summary of the number of 30 second epochs under Normal and Recovery (N/R) conditions (n = 21)

<table>
<thead>
<tr>
<th></th>
<th>W (N/R)</th>
<th>SREM (N/R)</th>
<th>S1 (N/R)</th>
<th>S2 (N/R)</th>
<th>SWS (N/R)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>58/35</td>
<td>218/206</td>
<td>61/45</td>
<td>449/468</td>
<td>217/272</td>
</tr>
<tr>
<td>SD</td>
<td>32/24</td>
<td>62/64</td>
<td>22/15</td>
<td>69/72</td>
<td>56/58</td>
</tr>
<tr>
<td>Median</td>
<td>52/26</td>
<td>209/229</td>
<td>61/48</td>
<td>439/460</td>
<td>226/278</td>
</tr>
<tr>
<td>Min</td>
<td>12/7</td>
<td>104/98</td>
<td>12/13</td>
<td>326/364</td>
<td>121/123</td>
</tr>
<tr>
<td>Max</td>
<td>123/87</td>
<td>318/318</td>
<td>102/79</td>
<td>608/619</td>
<td>330/373</td>
</tr>
</tbody>
</table>

For testing the SWS-hypothesis, Figure 4e offers essential information. Visual comparison of the stage counts suggests there was more SWS during Recovery nights than Normal nights. This confirms the SWS-hypothesis, at least based on this data.

Figure 5 presents the means and the standard deviation (SD) of epoch counts. The most common stage is S2, which we can also see from Figure 4. Again, there was a difference in SWS between Normal and Recovery conditions. This difference seems to be proportionally clearest among the stages.

After visually examining the distributions of stage counts, we proceed to results of statistical testing. The SWS-hypothesis is tested by pairwise comparison of stage count data. These results were then compared with the transition probabilities of the Markov matrix. Besides this, statistical dependencies between stage transitions (not only SWS) were investigated.

Table 3 includes the differences of stage counts under the two conditions. The value of the Normal night is subtracted from that of the Recovery night. Note that here the percentage values are differences of relative frequencies, not percentage changes between the two conditions. For example, subject 2 had a difference of -9 in SREM stage between Normal and Recovery conditions. The reported percentage value 1% was the difference of the relative frequencies (26.5% for Normal and 27.6% for Recovery) of the SREM stage. The relative or absolute frequencies are not reported in the table, only their differences. Likewise, the percentage change for subject 2 in SREM would be 11% as it increases from 263 (Normal) to 292 (Recovery).

The results of the Wilcoxon Rank test (confidence interval 95%) are reported in Table 4. The test showed that there were statistically significant differences
Figure 5: Distribution of the mean numbers (SD) of sleep stages under Normal and Recovery conditions
### Table 3: Stage count differences between Normal and Recovery conditions

<table>
<thead>
<tr>
<th>Subject</th>
<th>W</th>
<th>SREM</th>
<th>S1</th>
<th>S2</th>
<th>SWS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-6</td>
<td>-6</td>
<td>-38</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>-9</td>
<td>-9</td>
<td>-46</td>
<td>63</td>
<td>29</td>
</tr>
<tr>
<td>3</td>
<td>-12</td>
<td>-12</td>
<td>-20</td>
<td>101</td>
<td>67</td>
</tr>
<tr>
<td>4</td>
<td>14</td>
<td>14</td>
<td>7</td>
<td>-26</td>
<td>63</td>
</tr>
<tr>
<td>5</td>
<td>-15</td>
<td>-15</td>
<td>-48</td>
<td>70</td>
<td>83</td>
</tr>
<tr>
<td>8</td>
<td>-68</td>
<td>-68</td>
<td>-11</td>
<td>40</td>
<td>101</td>
</tr>
<tr>
<td>9</td>
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<td>-37</td>
<td>-25</td>
<td>-16</td>
<td>47</td>
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<tr>
<td>10</td>
<td>13</td>
<td>13</td>
<td>34</td>
<td>60</td>
<td>69</td>
</tr>
<tr>
<td>11</td>
<td>-27</td>
<td>-27</td>
<td>-5</td>
<td>-24</td>
<td>143</td>
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<tr>
<td>12</td>
<td>-67</td>
<td>-67</td>
<td>-35</td>
<td>-11</td>
<td>100</td>
</tr>
<tr>
<td>13</td>
<td>-3</td>
<td>-3</td>
<td>3</td>
<td>-42</td>
<td>96</td>
</tr>
<tr>
<td>14</td>
<td>6</td>
<td>6</td>
<td>-41</td>
<td>134</td>
<td>-18</td>
</tr>
<tr>
<td>15</td>
<td>-108</td>
<td>-108</td>
<td>-22</td>
<td>4</td>
<td>74</td>
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<tr>
<td>16</td>
<td>-2</td>
<td>-2</td>
<td>-53</td>
<td>43</td>
<td>40</td>
</tr>
<tr>
<td>17</td>
<td>4</td>
<td>4</td>
<td>-17</td>
<td>-62</td>
<td>83</td>
</tr>
<tr>
<td>18</td>
<td>15</td>
<td>15</td>
<td>-8</td>
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<td>19</td>
<td>-24</td>
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<td>42</td>
</tr>
<tr>
<td>20</td>
<td>-76</td>
<td>-76</td>
<td>3</td>
<td>71</td>
<td>29</td>
</tr>
<tr>
<td>21</td>
<td>-8</td>
<td>-8</td>
<td>1</td>
<td>32</td>
<td>17</td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td>-23.5</td>
<td>-11.6</td>
<td>-15.4</td>
<td>19.38</td>
<td>55</td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td>33.87</td>
<td>52.45</td>
<td>23.07</td>
<td>58.06</td>
<td>40.17</td>
</tr>
<tr>
<td><strong>Median</strong></td>
<td>-12</td>
<td>-7</td>
<td>-17</td>
<td>9</td>
<td>63</td>
</tr>
<tr>
<td><strong>Min</strong></td>
<td>-108</td>
<td>-104</td>
<td>-53</td>
<td>-79</td>
<td>-18</td>
</tr>
<tr>
<td><strong>Max</strong></td>
<td>15</td>
<td>86</td>
<td>34</td>
<td>134</td>
<td>143</td>
</tr>
</tbody>
</table>
Table 4: Statistical testing of stage count differences between Normal and Recovery conditions

<table>
<thead>
<tr>
<th>Test Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>W **</td>
<td>28</td>
</tr>
<tr>
<td>SREM</td>
<td>72</td>
</tr>
<tr>
<td>S1 **</td>
<td>37</td>
</tr>
<tr>
<td>S2</td>
<td>133</td>
</tr>
<tr>
<td>SWS ***</td>
<td>223</td>
</tr>
</tbody>
</table>

Wilcoxon Signed Rank test for paired data, * equals p < 0.05, ** p < 0.01, and *** p < 0.001

Table 5: Comparison of the probability matrices under the two conditions N(R)

<table>
<thead>
<tr>
<th></th>
<th>W</th>
<th>SREM</th>
<th>S1</th>
<th>S2</th>
<th>SWS</th>
</tr>
</thead>
<tbody>
<tr>
<td>W</td>
<td>66%(49%)**</td>
<td>2%(4%)</td>
<td>23%(28%)</td>
<td>9%(18%)*</td>
<td>0%(2%)</td>
</tr>
<tr>
<td>SREM</td>
<td>2%(2%)</td>
<td>95%(95%)</td>
<td>2%(2%)</td>
<td>1%(2%)**</td>
<td>0%(0%)</td>
</tr>
<tr>
<td>S1</td>
<td>7%(6%)</td>
<td>4%(4%)</td>
<td>49%(48%)</td>
<td>40%(41%)</td>
<td>0%(0%)</td>
</tr>
<tr>
<td>S2</td>
<td>2%(2%)</td>
<td>1%(2%)</td>
<td>3%(2%)*</td>
<td>88%(88%)</td>
<td>5%(6%)</td>
</tr>
<tr>
<td>SWS</td>
<td>1%(1%)</td>
<td>0%(0%)</td>
<td>0%(0%)</td>
<td>10%(10%)</td>
<td>89%(89%)</td>
</tr>
</tbody>
</table>

Wilcoxon Signed Rank test for paired data, * equals p < 0.05, ** p < 0.01, and *** p < 0.001

between stage counts under the two conditions. The difference of SREM was not statistically significant (p = 0.137). On the other hand, the difference of the amount of W stages was clear (p = 0.001). S2 was the most common stage under both Normal and Recovery conditions. This can lessen the significance of the difference (p = 0.5621). Finally, the SWS hypothesis seems to hold (p < 0.001). This would confirm the inference made earlier (see Figure 4e).

The probability of transitions between stages is estimated by forming two Markov matrices, which are combined in Table 5. The number of transitions were divided by the sum of the transitions from a given stage. This model gives us information about the structure of the transition process. Table 5 presents estimated probabilities for Normal and Recovery conditions. Also, the results of the statistical comparison are given.

There were 25 possible transitions. Four transitions (W→W, W→S2, SREM→S2, and S2→S1) differed in a statistically significant manner between Normal
and Recovery conditions. In $W \rightarrow W$ and $S_2 \rightarrow S_1$, the probability was greater under the Normal condition. This also held for $SWS \rightarrow S_1$, but the difference was not statistically significant. In all the other 22 transitions, the probability was greater under Recovery conditions. The difference was greatest in $W \rightarrow W$ transitions (66% for N and 49% for R). This was balanced by a decrease in the probability of $W \rightarrow S_2$ transitions (9% for N and 18% for R). The changes between conditions in the $W$-row matrix (transitions from $W$) were more numerous than in other rows.

Earlier in this section, the SWS-hypothesis was analyzed. The difference between conditions in the amount of epochs was greatest in the SWS stage. This held for both the absolute proportional change (see Table 3). Now the interesting question is, how does this affect probabilities of SWS transitions? Surprisingly, Table 5 shows that the SWS row (transitions from SWS) was unaffected. Thus the increase of SWS under Recovery conditions did not seem to lead to any clear changes in the probabilities of transitions from and to the SWS stage. Further analysis could focus on the interaction of $W$ and SWS stages as they seem to react differences of conditions more actively than other stages.

6 Discussion

In this study, the structure of sleep was studied under two conditions, Normal and Recovery. The first method was the comparison of epoch counts. The second was using a Markov chain model to describe the probability of transitions between sleep stages. Both were applications of existing theories.

Firstly, the comparison of epoch counts showed that there were more SWS epochs under the Recovery conditions than Normal conditions. This confirmed the SWS-hypothesis. It seems then natural to conjure that there would be more $SWS \rightarrow SWS$ transitions under the Recovery conditions. However, this was not the case. The Markovian approach showed that the statistically significant transition differences were in $W \rightarrow W$ and $W \rightarrow S_2$, $W \rightarrow SWS$, $SREM \rightarrow S_2$, and $S_2 \rightarrow S_1$. Under the Recovery conditions there were fewer $W$ epochs, i.e. the subject has slept more. Two out of the four differences occurred in transitions from the $W$ stage. Thus the interaction of $W$ with other stages was more evident than that of SWS. This calls for further investigation.

The different behavior of the epoch count and transition probabilities of SWS
are examples of new knowledge that can be obtained by using a Markov chain approach. However, the model used here is relatively simple when compared with continuous-time Markov models reported in the literature. Introducing a unique matrix for each epoch as opposed to just one for the whole night would be a major change. Also, other more powerful properties of the Markovian theory could be used. For example, the question of when the SWS stage is first reached is interesting. However, in order to benefit from these measures, research questions and perhaps also the study design would need changes. The clearest differences between conditions can be perhaps detected with a simple model, like the one used here. Creating simulated hypnograms with this model is not very meaningful, because they would not provide new information about the process. The situation is different with a multiple-matrix, i.e. a continuous-time model, where the properties of the process cannot be calculated directly from the transition probability matrices.

One limitation of this study is that there are only two conditions (Normal and Recovery). A possible way to expand the area of study is to increase the number of testing conditions. Sleep disorders, sex, age etc. could be valuable conditions for assessing the structure of sleep. This would give more information about the sleep structure under different conditions. Furthermore, the reasonability of the whole Markovian approach could be assessed. If the Markov model suggests new ideas that can be tested empirically, it contributes to the development of sleep science. Clinical work is a prime example. By supplementing traditional hypnograms, Markov matrices can perhaps help to diagnose pathologies by providing more detailed information about transitions between sleep stages. However, it takes time for the sleep medicine community to accept new practices. Results should be more thoroughly interpreted in the light of current sleep research theories, a task beyond the scope of this special study [15].
References


