Investigating scheduling of work: a two-stage optimal matching analysis of workdays and workweeks

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Summary. We study the scheduling of work by using optimal matching analysis. We show that optimal matching can be adapted to the number of periodicities and theoretical concerns of the topic by adjusting its costs and parameters. Optimal matching is applied at two stages to define workdays and workweeks at the first and second stage respectively. There were five types of workdays and seven types of workweeks in the UK between 2000 and 2001. Standard workdays represented just over a half of workdays and standard workweeks constituted one in four workweeks. There were three types of part-time workweeks.

Keywords: Cost; Optimal matching; Time use; Two-stage optimal matching; Work schedule; Work time

1. Introduction

Work time is an important dimension of quality of life and social stratification. Trends in work time reflect changes in the structure of society. Nevertheless, research on work time trends has focused predominantly on the duration, rather than the scheduling, of work. This is partly due to the lack of suitable data and technique of analysis. In this paper, we introduce a statistical technique that is useful for analysing the scheduling of time use. We call this technique ‘two-stage optimal matching’. We employ it for the analysis of 7-day diary data from the UK 2000–2001 Time Use Survey (Office for National Statistics, 2003) to define a typology of workweeks.

Research focusing on the duration of work has found that the average work time has decreased since the 1960s in industrialized countries, and that leisure time has been on the rise in the same period (Dumazedier, 1967; Gershuny, 2000; Robinson and Godbey, 1999). However, it has also been reported that the decrease in work time has been the most prevalent among low earning and low status workers. For higher grade professionals and managers, their work time has increased over the same period. These two opposite trends in work time have reversed the social class–work time gradient in the 1960s, so that, at the beginning of the 2000s, high skilled workers have longer work hours than unskilled workers (Gershuny, 2000).

Few studies have focused on the scheduling of work. To analyse work schedules, it is more appropriate to use data that have been collected by diary methods as opposed to stylized questions...
in surveys, which request respondents to estimate their usual weekly work hours by direct questioning. Time diary data are usually collected by respondents’ records of their activities at every 10-min or 15-min time slots. Unlike stylized questionnaire data, these data not only provide information on the amount of time that is spent on daily activities but also the scheduling of these activities.

In sociology, Szalai (1972) first explored the timing of daily activities by graphical representations of time diary data. In economic research, Hamermesh (1999, 2002) examined the changes in the proportion of workers working at different times over the day in the USA from 1973 to 1991. He found a decline in evening and night shifts in that period, but it occurred mostly to high wage workers. He also reported a decline in synchronicity in spouses’ work schedules after the 1970s.

However, the studies that were reviewed above focus on the proportion of the population’s work time at different timings of the day, rather than looking into how work is distributed within an individual workday. This is mainly due to the lack of suitable methods to analyse individual work time patterns. In fact, the scheduling dimension of time use data had not been thoroughly analysed until optimal matching (OM) analysis, which is a method for analysing sequences of events, was introduced into social science research (Abbott and Forrest, 1986).

Wilson (1998) first applied OM to time diary data to explore the timing of daily activities. Lesnard (2004) introduced dynamic Hamming matching (DHM), which is an advanced version of OM, that was adapted specifically to analyse time use data. On the basis of DHM, researchers have identified a variety of types of workday in France (Lesnard, 2006a) and in Belgium (Glorieux et al., 2008). The types are shift, which include morning, evening or night shifts, fragmented—two short work spells with a long break between them, short—a short spell of work, standard—a 9 a.m. to 5 p.m. period of working hours, and long—a long working episode. In France, standard workdays increasingly gave way to non-standard work schedules between the 1980s and the 1990s. Lesnard (2008) suggested that the expansion of non-standard workdays is one of the key factors that explains the increase in desynchronization of work time for dual earn er couples.

Yet most studies that investigate the scheduling of work are confined to 1-day diary data, despite the fact that work is probably organized according to longer timeframes—1 week at least. Average workweek time is regularly measured and reported in official labour statistics, which are usually based on stylized time use data collected in labour force surveys. The number of weekly work hours is also a topic of frequent debates and negotiations among policy makers, trade unions and academics. Nevertheless, relatively little attention has been given to scheduling of work hours over the week. Since most time use surveys collect only day long rather than week long diaries, the analysis of workweek schedules has been restricted by the lack of suitable data. Furthermore, analysing the scheduling of work over the week is methodologically more challenging than focusing on workdays because it requires accounting for the scheduling of work hours within the day, as well as workdays over the week.

Following the recent Eurostat guidelines on collecting time use data, some recent national time use surveys, including UK 2000, France 1999, Belgium 1999 and Finland 2000, have collected 7-day working time data by using the ‘workweek grid’ method (Robinson et al., 2002). Week long time use data provide researchers with the opportunity to investigate patterns of work schedules; however, very few studies have done so by using advanced statistical techniques. For example, when examining individuals’ workweeks and the synchronicity of work time of dual earner couples, Chenu and Robinson (2002) adopted a series of indicators and numeric indices such as the length of workweek and the amount of work during weekends to analyse individual
workweeks, but they did not employ systematic methods for contrasting differences in profiles between different types of workweeks, or between partners’ work time.

This paper aims to fill the methodological and empirical gaps in the literature with respect to work time. Section 2 provides the background of OM and explains its cost setting procedure. Section 3 describes the data that are used and the procedures taken to adapt OM for the analysis of workdays and workweeks. Section 4 presents the findings. Section 5 concludes.

2. Optimal matching analysis

2.1. Definitions and concepts

Methods for describing sequential data, e.g. data concerning life cycle events, and career trajectories, have been available to social scientists for more than three decades. Among these methods, OM analysis has been the most popular and was introduced to the social sciences by Abbott and his colleagues in the 1980s (Abbott and Forrest (1986) and Abbott and Hrycak (1990); see Abbott and Tsay (2000) for a detailed review). In recent years, some alternative approaches to sequence analyses have also been proposed (see Elzinga (2003)).

OM is a distance measure adapted to sequence data. Each sequence consists of events, which are coded as alphabetical or numerical states for analysis. For example, in the case of daily activity sequences, researchers can code all work and work-related events as ‘1’ and all other events such as sleeping and leisure as ‘0’. A 15-min slot time use day diary will have 96 states each equalling 1 or 0. The dissimilarity between each pair of sequences is defined as the minimum ‘cost’ to transform one into the other so that all states of the two sequences are matched (Durbin et al., 1998; Kruskal, 1983). Three operations are allowed in the matching process: insertion, deletion and substitution. Each of the operations is assigned a cost. The total cost of matching of the two sequences is the minimum sum of the cost for all the transformations of states required. The type and the number of transformations that are used depend on the relative cost of either insertion or deletion compared with substitution, which is discussed in detail below. Insertion and deletion, which are commonly called ‘indel’, are completely symmetrical in OM and are therefore often given the same cost. The dissimilarity matrix of all pairwise comparisons between sequences is used as the base for clustering analysis to derive typologies of sequences.

2.2. Cost setting

A major issue in applying OM to social science research is how to set the cost for each of the transformations. Although OM has been used for more than three decades, users are often uncertain about how different cost settings might affect the results (Wu, 2000). Stovel et al. (1996) stated that ‘The assignment of transformation costs haunts all optimal matching analyses’. Statistical software in the early 1980s was not yet well adapted for analysing sequence data, and empirical data analyses usually took many hours to complete. It was difficult to test in sensitivity analyses how different values of cost might lead to different results. Considerable progress has been made on this issue with the developments in relevant statistical packages and programs. Furthermore, social scientists have increasingly been employing, experimenting with and reflecting on OM.

One way to set the cost is to start with theoretical concerns regarding the topic of investigation. Sequence data are usually concerned with events and time, which determine how the two kinds of operations, i.e. indel and substitutions, are used in OM. When indels are used, the emphasis is placed on the matching of identical sets of events rather than on the timing of these events, because the operations will necessarily alter the timing structure of the original
sequence. Indels change the timing structure of a sequence, or ‘warp time’ (Abbott and Tsay, 2000). To illustrate this, let us consider two sequences: 011100 and 000111. We may convert the first into the second by inserting 00 in front of the first state and delete the last two 0s. We may also do so by substituting 0 for the second and the third 1s, and 1 for the last two 0s. In the first case, the emphasis is placed on the identical set of events 0111 but the timing of these events is ‘simplified’. In the second approach, which involves only substitutions, the focus is on comparing the contemporaneous but distinct events (Lesnard and Saint Pol, 2006) so that the events, rather than timing, are simplified. The ratio of indel to substitution costs determines whether it is preferable to simplify the timing or the events when comparing pairs of sequences. In fact, what is now commonly known as OM was originally a refinement that was suggested by Levenshtein (1966) to improve the distance measure that had been introduced by Hamming (1950), who measured similarity of sequences by the number of identical contemporaneous events.

Table 1 presents the three types of OM distance measures that were suggested by Hamming and Levenshtein. For the Hamming distance measure, only substitutions are used and the cost for substitution equals 1. In the Levenshtein I measure, both substitutions and indels are allowed, and the cost for each is equal to 1. In the Levenshtein II measure, only insertions and deletions are used and the cost of each equals 1. The Levenshtein II measure can also be obtained by setting the indel cost equal to 1 and substitution equal to 2.

Fig. 1 illustrates how users might adjust the ratio of indel to substitution costs to highlight the relative importance of the timing vis-à-vis that of events in the sequences. If the cost for substituting two events is higher than that for one insertion and one deletion, then substitutions are never used (Kruskal, 1983). When no substitution operations are used, because they are not allowed by definition as in the Levenshtein II distance or their cost is greater than twice the indel cost, OM is equivalent to finding the longest common subsequence (Kruskal, 1983). When no indel operations are used, because they are not allowed by definition as in Hamming distance or their cost is much greater than the substitution cost, OM amounts to counting the number

Table 1. Three types of OM distances

<table>
<thead>
<tr>
<th>Measure</th>
<th>Operations and costs</th>
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<tbody>
<tr>
<td></td>
<td>Substitution</td>
</tr>
<tr>
<td>Hamming</td>
<td>Yes (cost = 1)</td>
</tr>
<tr>
<td>Levenshtein I</td>
<td>Yes (cost = 1)</td>
</tr>
<tr>
<td>Levenshtein II</td>
<td>No (or cost ≥ 2)</td>
</tr>
</tbody>
</table>

Fig. 1. Patterns of sequences and the ratio of substitution to indel costs in OM
of dissimilar contemporaneous events. When indel operations are allowed but are suppressed by a high cost, they are used only when sequences are not of equal length. In such cases, the resulting dissimilarity is likely to be defined by the length of sequences. As a result, the ratio of indel to substitution costs determines the kind of distance measure that OM will be most sensitive to. If the timing of events is not important, users should favour costs that are close to the Levenshtein II measure. In contrast, high indel costs should be used when timing is important for the analysis. Users should set the same cost for indel and substitution if they want to use both kinds of operations in a more or less balanced way (Lesnard, 2010).

Apart from the three OM distance measures that are described in Table 1, it is common, especially in social research, to allow the substitution cost to vary with each pair of states. Let us take three-state time use sequences, rest–leisure–work sequences, as an example. Suppose that we code all activities into rest, leisure or work. The substitution costs for each pair of states, namely, rest–work, work–rest, work–leisure, leisure–rest, and so on, can be different from one another. This approach makes it possible to have some substitution costs that are higher as well as some lower than the indel costs. When the cost is higher, the two different events will not be substituted but the algorithm will try to shift the two sequences to find the identical but shifted subsequences. When the cost is lower, the two different events will be substituted and be kept at their original timing in synchronization. However, it should be noted that defining a substitution cost matrix, in which the substitution costs are weighted or changed according to each pair of states, amounts to deciding a priori that some pairs of states are closer to one another than others. This a priori knowledge can be informed by theory (e.g. Halpin and Chan (1998)), hypotheses (for an illustrative example, see Stovel et al. (1996)) or previous findings. It can also be informed by the distribution of the sequences. For example, frequencies of transitions between states have often been taken to be inversely proportional to the distance between states (Abbott and Hrycak, 1990).

We can adjust the substitution costs even more flexibly to different kinds of data and research questions. For example, Lesnard (2004, 2010) recommended a variant of Hamming matching called DHM, for analysing time diary data, where sequences are of equal length and it is important to preserve the timing structure of events. In DHM, only substitutions and no indels are used, and the substitution costs are defined according to the timing of events and are set to equal the inverse of the transitional frequencies of the pair of the states that are observed in the sample. Let us take a two-state case, work and non-work, as an example. The frequency of changing states from non-work to work is higher at 9 a.m. than at 9 p.m., as observed in the sample, and the substitution cost for non-work to work is, therefore, lower at 9 a.m. Indel costs are usually set relatively to substitution costs. Halpin (2010) recently introduced a variant of OM, in which the indel cost is inversely proportional to the spell length, i.e. the duration of a state.

The versatility of OM is also illustrated when it is applied to multiple-domain sequences, i.e. sequences that are composed of several distinct, but theoretically interdependent, domains such as family status, employment status and housing careers (Pollock, 2007). Although it is possible to conduct sequence analyses for each of the domains, a simpler way is to define matrices of substitution costs for each and then to combine them (Pollock, 2007; Stovel et al., 1996). This method is called multiple-sequence analysis. In Pollock’s (2007) study, the substitution cost concerning employment status, such as employed and self-employed, as well as housing tenure status, such as owning with a mortgage and owning outright, equal the sum of the substitution cost concerning employment status and those concerning housing tenure status. Hence sequence analysis of the multiple domains can be conducted by multiple OM analyses or by combining multiple substitution cost matrices for a single OM analysis. In the case of multiple OM analyses,
the domains are assumed to be independent of one another, although the correlations between them can be identified from the results. When combining multiple substitution cost matrices for a single OM analysis, the domains are assumed to be interdependent of one another.

As suggested by Abbott (2000), the hypotheses on which OM rests are not about how data are generated, but on the kinds of patterns that users expect to see before the analysis, i.e. the aim of the analysis is description rather than explaining the underlying processes. In standard OM, the ratio of substitution to indel costs can be adjusted to accommodate infinite combinations of patterns. As can be seen from Fig. 1, at one extreme, when the ratio is set to be the lowest and only substitutions are used, OM will identify the number of similar contemporaneous events in the sequences. At the other extreme, when the ratio is set to be the highest and only indels are used, OM will look for the longest common subsequence. The importance that is attached to the timing of sequences decreases with increases in the ratio. Focusing the analysis on a certain type of pattern does not imply, as unfairly criticized by Levine (2000) and Wu (2000), that OM will create *ex nihilo* this particular pattern. It just implies that the pattern being looked for will be easier to identify in the data if it exists. Using multiple substitution costs enables researchers to tune OM finely to suit the nature of the data and research questions.

As illustrated by multiple-sequence analysis, OM has great flexibility in its cost setting procedures to accommodate multiple-domain sequences. In what follows, we use workweeks as an example to demonstrate how OM can be adapted to the analysis of equal length long sequences involving multiple periodicities, i.e. workdays and workweeks.

### 3. Analysing workdays and workweeks

The data that are used for this study come from the UK 2000–2001 Time Use Survey which were collected by the Office for National Statistics from June 2000 to September 2001 (Office for National Statistics, 2003). The sample contains approximately 6400 households in the UK. The response rate was 61% for the household questionnaires and 73% for the subsequent diaries. All individuals aged 8 years or above in the households were requested to complete individual questionnaires and diaries. In addition to the traditional 2-day diaries, which comprise records of one weekday and one weekend, the UK Time Use Survey also collected 7-day workweek grid diaries. Time is divided into 96 15-min slots for each day of the workweek grid diaries. Respondents were requested to indicate their work or study episodes by drawing a line across the start and the end of each episode. They were also instructed to exclude travelling time and meal breaks from their work or study time.

The design of the diaries, however, does not enable users to distinguish between work and study spells. To build a typology of workweeks for the present study, only respondents in part-time or full-time employment, as reported in the household questionnaires, were selected. All full-time students were excluded from the analysis, although some of them might have had a part-time job. Of the 9823 respondents who filled in the week grid diaries, 4944 were in employment and recorded work time on at least one of the 7 days. In the workweeks, there are 21122 workdays in which respondents recorded at least one work episode.

Investigating workweek patterns involves analysing two nested periodicities: days within the week and hours within the day. At the level of the day, the focus is on the scheduling of work hours. At the level of the week, we are interested in how workdays are scheduled across the week. Although it is possible to apply OM directly to the 672 15-min time slots of the workweek grids, it will be more appropriate to take account of these two nested periodicities in the analysis as workers are likely to schedule their work time at two stages in real life. The issue of intraday work time variations over the week is similar to that of seasonality in time series analysis. As the
main goal of time series analysis is to model trends, such as the trend in rates of unemployment, seasonality is often considered to be irrelevant and controlled for by modelling it separately. In the case of scheduling of work hours within a day, intraday variation is a much more important issue than the case of seasonality in time series analysis, so it should be analysed separately.

Our approach is to apply OM in two steps, a method that we call two-stage OM. At the first stage, OM is applied to the 96 15-min time slots to define typologies of workdays. The sample consists of day long diaries with at least 15 min work time. There are repeated records from the same respondents who had more than 1 workday in the week. 21122 workdays are derived from the original 4944 workweeks. These sequences are made up of two states: work and non-work. Clustering analysis is applied to the dissimilarity matrix between workdays, which will be defined in the next paragraph, to produce a typology of workdays. At the second stage, OM is employed to analyse the 7-day weeks, which were made of the types of workdays that were identified in the first stage. The states include the types of workdays, which we shall discuss in the findings, and ‘rest’, which is a category to take into account the days with no work at all.

As mentioned in the previous section, the costs at the two stages should be set according to the importance of timing for the analysis. Focusing on timing is certainly crucial for the first stage, which is concerned with the scheduling of work time during the day. The parameterization for the substitution cost and the indel cost should be close to the Hamming distance measure, as illustrated in Fig. 1. We shall use a variant of the Hamming distance, DHM (Lesnard, 2004), which has been applied to the analysis of work schedules in recent studies (Glorieux et al., 2008; Lesnard, 2006a, b, 2008). In DHM, only substitution operations are used. To make the costs sensitive to the timing of sequences, their values are defined to be varying with the timing of the events and inversely proportional to transition frequencies between the pairs of states at a particular time as observed in the sample of workdays. The rationale for DHM is that transition frequencies between states reveal their relative distances at a given time $t$. A high frequency of transitions between any two states, e.g. work to non-work and non-work to work, at $t$ indicates that many individuals switch between the states at $t$ and, therefore, the likelihood that these two states belong to the same type of trajectory at $t$ is high. As a result, the distance between these two states is considered to be short. In contrast, a low frequency of transitions suggests that these two states belong to two different types of trajectory and hence the distance between them is considered to be long at $t$. DHM fits with the requirements of the first stage of the analysis. At the second stage, the timing of the states that is defined by the first stage results is crucial also. For example, working on an evening shift is likely to have different implications for social life on different days of the week. Thus DHM is also an appropriate parameterization for the second stage. We hence analyse workweeks with two-stage DHM. Fig. 2 summarizes our analyses.

At each of the two stages of the analysis, we employ the method ‘beta-flexible’ (Belbin et al., 1992; Milligan, 1989) to calculate the distance between groups as opposed to the original elements, which is called ‘linkage’ in clustering analysis. In beta-flexible linkage, the revised distance between a given cluster $k$ and a new group $(ij)$, which is formed by merging two clusters $i$ and $j$, depends on three components: the distance between $i$ and $k$, the distance between $j$ and $k$, and the distance between $i$ and $j$. All three distances depend on a parameter, $\beta$, which is the weight that is assigned to the distance between $i$ and $j$. The beta-flexible method has proved more robust in recovering structure in the presence of outliers and noise than other classical linkages such as Ward’s (Milligan, 1980, 1981). We conduct sequence analysis with the seqcomp plug-in for Stata, which is available free of charge at http://laurent.lesnard.free.fr. We used SAS for the clustering analysis because the beta-flexible linkage is not implemented in Stata.
4944 workweeks (2 states and 672 episodes)

21,122 workdays (2 states and 96 episodes)

13,486 days off

4944 simplified workweeks (6 states and 7 episodes)

5 types of workdays

1 type of day off

7 types of workweeks

Fig. 2. Synoptic representation of two-stage DHM for the analyses of workweeks

It is also possible to conduct the analyses with the TraMineR library in R (Gabadinho et al., 2008), which has implemented DHM since version 1.4 released on August 6th, 2009.

4. Findings

4.1. First stage

At the first stage of analysis, we focus on the 34,608 days in the 4944 weeks from the sample. 1078 out of the 34,608 days (3.11%) have missing values. Visual inspection reveals that these missing values appear to be coding errors, where ‘missing’ instead of 0s are coded for non-work spells during workdays and for all values during non-workdays. After these false missing values have been replaced with 0s, no further missing value is found.

We apply DHM to the 21,122 days with at least one work spell (61% of the days). Nevertheless the sample is too big for the 4 Gbytes memory limit that is imposed by 32-bit systems of our computers. We thus split these 21,122 days into two subsamples and conduct two analyses separately. The sample is randomized before being split. Agglomerative hierarchical clustering (linkage: beta-flexible with $\beta = -0.3$) is applied to the two distance matrices that are produced
by DHM. There are no definitive criteria to determine the number of clusters, but the ‘elbow criterion’ usually gives interesting starting points. An elbow, or a spike, in the intergroup distance indicates that two very dissimilar clusters have been merged. Therefore the cluster solution just before this merging should be considered rather than the one just after. In both samples, the first significant spike in the intergroup distance occurs for the seven-group partition, suggesting that very dissimilar groups have been joined and that there are at least eight types of workdays in the data. Another smaller spike is observed in the nine-cluster solution of the second sample. We examine and compare visual representations of the clusters and summary statistics of the different partitions between 11 and eight groups; average total work time, medians of the start and the middle and the end time of the workday.

Finally, we adopt the 10-cluster solution as it is the most succinct that incorporates all major types of part-time workdays, which are important characteristics of the UK workdays, and all the other major categories. We then match identical clusters in the typologies from the two samples based on tempograms, i.e. graphical representations of the state distribution for each time slot, and summary statistics. This step has been straightforward as the types of workdays that are identified from the two randomized subsamples are highly similar to each other, and to typologies that have been found from previous studies (Glorieux et al., 2008; Lesnard, 2006a, 2009). The final typology is summarized in Table 2 and represented graphically in Fig. 3.

The first two types are standard workdays (type 1, clusters 1 and 2). The first, which is also the most common type of workday in the UK, is the traditional 9 a.m. to 5 p.m. workday. The second type of standard workday is a variant of the 9 a.m. to 5 p.m. workday, but the starting time and the end time are both 1 h earlier. We hence call it the 8 a.m. to 4 p.m. workday. Although standard workdays are the most common type of work schedule, they account for only just over half of the workdays in the UK (52.1%). Other types of workdays deviate from the standard workdays in two main ways: length and timing. Type 2 workdays—long workdays (clusters 3 and 4)—have distinctly longer total work time, which is over 10 h. There are minor differences between them: the former is a longer version of the 9 a.m. to 5 p.m. workday and the latter is characterized by evening work in the workplace or at home. Long workdays constitute 15.5% of total workdays. There are three groups of shorter workdays: two of them are part-time workdays (type 4, clusters 8 and 9), which make up 14.3% of the total workdays. They have the major work spell in the morning or in the evening. The third type—short workdays (type 5, cluster 10)—have very short total work time and are characterized by multiple, short and staggered work spells. Short workdays represent 4.6% of total workdays. The final type—shift

<table>
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<th>Name</th>
<th>Size (%)</th>
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</tr>
<tr>
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<td>2</td>
<td>Standard</td>
<td>17.21</td>
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<tr>
<td>3</td>
<td>3</td>
<td>Long</td>
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<td>4</td>
<td>4</td>
<td>Long</td>
<td>4.78</td>
</tr>
<tr>
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<td>Shift</td>
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<td>Shift</td>
<td>3.03</td>
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<tr>
<td>4</td>
<td>8</td>
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<td>9</td>
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<td>Part time</td>
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</tr>
<tr>
<td>5</td>
<td>10</td>
<td>Short</td>
<td>4.56</td>
</tr>
</tbody>
</table>
Fig. 3. Tempograms of the typology of workdays: (a) cluster 1, \(N = 7375\) (34.9%), 9 a.m. to 5 p.m.; (b) cluster 2, \(N = 3636\) (17.2%), 8 a.m. to 4 p.m.; (c) cluster 3, \(N = 2273\) (10.8%), long; (d) cluster 4, \(N = 1010\) (4.8%), long day and evening; (e) cluster 5, \(N = 1405\) (6.7%), morning shift; (f) cluster 6, \(N = 791\), evening shift; (g) cluster 7, \(N = 641\) (3%), night shift; (h) cluster 8, \(N = 977\), part-time morning; (i) cluster 9, \(N = 987\) (4.7%), part-time afternoon; (j) cluster 10, \(N = 964\) (4.6%), short atypical

workdays (type 3, clusters 5–7)—depart from the standard workdays in their timing of work. There are three types of shifts: morning, evening and night, which add up to 13.4% of the total workdays. The total work time of these shift workdays is virtually the same as the standard workday work time. However, most of the work on these days is carried out before 9 a.m. or after 5 p.m. Interestingly, the morning shift is the most common among the three types of shift workdays, whereas the night shift is the least common form.

To build simplified workweeks, we employ a five-category typology as described in the above paragraph and in Table 2. Furthermore, we add the category rest days to take account of the days that contain no work spell. Thus, every week contains seven episodes from Monday to
Sunday and six states: five types of workday and one type of rest day. The visual representation of these simplified workweeks is given in Fig. 4. The proportion of each of the five types of workdays remain virtually stable during weekdays. Standard workdays make up about 40% of the weekdays. As expected, the results are very different during weekends. Work is uncommon on Saturdays and Sundays. It is worth mentioning that the proportion of non-standard workdays, namely shift, part-time and short workdays, is much higher on weekends than on weekdays, i.e. weekend work is atypical, and the types of workdays on weekends are more likely to be atypical as well.

4.2. Second stage
To build a typology of workweeks, we run DHM on these simplified workweeks. In Fig. 5, the intergroup distances for the series of nested partitions indicate that there are at least five types of workweeks. Two other, smaller, spikes occur at the 10-cluster and 18-cluster solutions. The results suggest that we should examine the series of partitions ranging from 18 to 5.

We first try to reduce the number of groups starting from the 18-group solution that was suggested by the clustering analysis using the beta-flexible method. However, some of the groupings that are suggested do not seem appropriate. For instance, the first grouping suggested that we combine is clusters 5 and 16. We therefore decided to reduce the number of groups manually on the basis of descriptive statistics and visual representations of the cluster solutions. Clustering analysis is basically an algorithm that is used to produce nested sets of clusters. As an algorithmic method, it is based on the repetition of a finite sequence of simple and intuitive instructions. In the beginning, each element is a separate cluster and on each step the two closest clusters

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**Fig. 4.** Simplified workweeks: ■, standard; □, long; ▌, shift; ▄, part time; ▅, short; ▼, rest
are merged, whereas closeness depends on both the distance measure and the linkage that is chosen. This sequence of instructions could be done manually, though it is much more efficient to run it by computers. However, efficiency comes at the expense of rigid rules which may not be entirely satisfactory for the last steps of grouping. For the last few steps of the agglomerative clustering, successive groupings that were suggested by the algorithm are not theoretically or empirically satisfactory. We therefore conduct the grouping by linking clusters that are similar in theoretically important characteristics, such as the number of workdays, the proportion of work done on weekends and the total work hours. To adopt results that are different from those suggested by the algorithm, however, one must provide convincing arguments and justifications.

Fig. 6 shows the 18-cluster solution. Table 3 displays descriptive statistics on the 18 clusters and how we have reorganized them. Cluster 2 represents the standard workweek of 9 a.m. to 5 p.m., Monday to Friday. We combine clusters 8, 10, 13, 14 and 16 into a single category—long workweek—because they are all characterized by long work hours over the week. Although cluster 10 is also characterized by a high proportion of weekend work, as illustrated in Fig. 3, this cluster is very close to the other clusters in terms of the long duration of work on each workday. The average workweek time is longer than 45 h, and in three of them it is over 48 h, i.e. the maximum limit that is suggested by the European working time directives. We then group clusters 6, 7 and 15 because they all contain shift workweeks consisting of shift hours on workdays. Clusters 9 and 12 form another category—alternate workweeks—in the new typology. Unlike other types of workweeks, they are not composed of a uniform type of workdays. Instead,
the types of workdays vary across the week, e.g. standard hours on Monday, shift hours on Tuesday, part-time work on Wednesday, and so on.

The rest of the clusters are variants of short and part-time workweeks. First, for clusters 11 and 17, individuals usually work on weekdays but tend to have part-time work hours on each of the workdays. We label this group part workday workweek. Another type of part-time work is found in clusters 4 and 5, where respondents take 1 or \( \frac{1}{2} \) a day off during weekdays but tend to work at standard hours during their workdays. These clusters are grouped and called standard
workday part time. The final type is that of a short workweek consisting of clusters 1, 3 and 18 that have only around 3 workdays in a week.

Descriptions of the seven-group typology of workweeks are provided in Fig. 7 and Table 4. Type A—standard workweeks—are composed of five standard workdays from Monday to Friday and the average work time is 42.2 h. Although standard workweeks are the most common type, they account for only about a quarter (26%) of the total workweeks. Another common type, type B—long workweeks—make up a fifth of the total workweeks. Long workweeks are composed of one or more long workdays. The average work hours are 10 h longer than the standard workweeks. In addition, they deviate from standard workweeks in the timing of work; 13% of them contain weekend work compared with 4% for standard workweeks.

Type C—shift workweeks—constitute 12% of the total workweeks. Like long workweeks, they have a high proportion of weekend work (12%). The average work time is shorter than a standard workweek (37.7 h). From the cluster (cluster 4, Fig. 7), we see that, if Saturday or Sunday is a workday, a rest day will take place between Monday and Friday. In other words, shift workweeks are not only characterized by shift hours of work, but also a shift of the days off from weekends to weekdays.

Alternate workweeks—type D—are made of more than one type of workdays. There is a high proportion of part-time workdays and hence the average weekly work time is considerably short (31.7 h). Weekend work is also common in this type of workweek (12.3%). Accordingly, days off tend to be shifted towards Monday to Friday. It is well documented that the part-time work rate is relatively high in the UK compared with other developed countries. In the present study, we have identified two main types of part-time workweeks, which together form about a fifth of the total workweeks. Type E—standard workday part time—is similar to the standard workweek but is characterized by roughly one more day off (2.5 compared with 1.8 days). Type F—part workday part time—is characterized by part workweek (2.7 days off on average) and part-time work hours during workdays. Types E and F of part-time workweeks have average

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†Number of workweeks in the sample, 4944.
Fig. 7. Final typology of workweeks (■, standard; □, long; □, shift; □, part time; □, short; □, rest): (a) cluster A, $N = 1160$ (26.1%), standard; (b) cluster B, $N = 888$ (20%), long; (c) cluster C, $N = 538$ (12.1%), shift; (d) cluster D, $N = 309$ (7%), alternate; (e) cluster E, $N = 406$ (9.1%), part time I; (f) cluster F, $N = 462$ (10.4%), part time II; (g) cluster G, $N = 682$ (15.3%), short

total work hours of 21.1 and 34.3 respectively, which are both shorter than standard workweeks. Furthermore, weekend work is more common than standard workweek, especially working on Saturdays. These results are consistent with previous studies on work time trends, which show that long and short workdays are both increasingly common in economically advanced societies (Gershuny, 2000). Our typology goes further to identify the distribution of workdays across the week, and that working on weekends is a key characteristic of work time trends.

Finally, type G—short workweeks—which represent 15% of the workweeks, are composed of only 3 workdays. Nevertheless, standard work hours are usually involved during workdays.
Table 4. Descriptive statistics of the final typology of workweeks†

<table>
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<tr>
<th>Cluster</th>
<th>Name</th>
<th>% of workweeks</th>
<th>Work time (h)</th>
<th>Number of days off</th>
<th>Number of workdays</th>
<th>% work on Saturday</th>
<th>% work on Sunday</th>
<th>% work on weekend</th>
<th>% full Saturday off</th>
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<td>1.7</td>
<td>5.3</td>
<td>13.5</td>
<td>11.1</td>
<td>12.3</td>
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</tr>
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<tr>
<td>G</td>
<td>Short</td>
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<td>8.6</td>
<td>9.6</td>
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</table>

†Number of workweeks in the sample, 4944.

The average weekly work hours are short (21.6 h). In fact, short workweeks can also be defined as a variant of part-time work in the UK. Similarly to types E and F, there is a high proportion of weekend work (9.6%).

To assess the effectiveness of two-stage OM, we present the typology using the 672 15-min episodes in Fig. 8. The characteristics of the seven types of workweeks are the same as those illustrated in Fig. 7 and Table 4. Nevertheless, it is much more difficult to tell the distinctions between them from Fig. 8 alone. Hence, the results would have been much more difficult to interpret if we had not obtained the first-stage results. The strength of two-stage OM lies in making the interpretation of results easier. It should be noted that applying OM directly on the 672 15-min episodes yields slightly different results from two-stage OM. Overall, however, the difference should not be significant because the first-stage is guided by theory and the empirical findings of previous studies. The additional figure is available on request from the authors.

4.3. Advantages of analysing both workdays and workweeks

As can be seen from Fig. 7, workweeks are usually dominated by one type of workdays; for example, long workweeks are composed of mostly long workdays, and shift workdays are common in shift workweeks. This suggests that work is not randomly scheduled over days and weeks but is instead highly temporally structured. Previous research demonstrated that work schedules mostly reflect the preferences of the employers rather than those of the employees. In France and in the USA, employees who reported having control over their work schedules were less likely to work shift, part-time and other non-standard hours than other employees (Golden, 2001; Lesnard, 2008).

The limited variation in the types of workdays within a workweek gives some confidence to researchers who only have day long time use data; analysing how work is organized at the level of the day is likely to give good insights into how work is scheduled over a longer period. Our findings also show that there is one major drawback from this approach: the overall proportion of atypical or non-standard workweeks will be underestimated if the figures are generalized from the analysis of workdays alone. This is because standard workdays, though not the dominant type of workdays, occur also in long, shift and all types of part-time workweeks. In other words, observing a standard workday in a sample is not a good predictor of whether or not the rest of the week will be made of only standard workdays. In contrast, a non-standard workday is a fairly good predictor of atypical workweeks.
Fig. 8. Tempograms of the final typology of workweeks (15-min time slots): (a) cluster A, \( N = 1160 \) (26.1%), standard; (b) cluster B, \( N = 888 \) (20%), long; (c) cluster C, \( N = 538 \) (12.1%), shift; (d) cluster D, \( N = 309 \) (7%), alternate; (e) cluster E, \( N = 406 \) (9.1%), part time I; (f) cluster F, \( N = 462 \) (10.4%), part time II; (g) cluster G, \( N = 682 \) (15.3%), short

Thus, researchers will overestimate the proportion of standard workweeks on the basis of the number and proportion of standard workdays in their samples. In this study, 52% of workdays are standard, or 31% when both workdays and rest days are taken into account, whereas standard workweeks account for only 26% of the total workweeks. In contrast, long workdays represent 16% of the workdays but 20% of the workweeks are long. In sum, the proportion of
workweeks will be more accurately represented if the analyses are conducted at both the day and the week levels, rather than solely at the day level.

5. Conclusion

We have demonstrated that two-stage OM can be usefully applied to the analysis of workdays and workweeks. Our study improves on past studies by providing important insights into the schedule of work hours within workdays and the structure of work days across the week. We have identified five types of workdays and seven types of workweeks and more varieties of part-time work in the UK. Standard workdays constituted just over a half of total workdays, and standard workweeks represented about a quarter of workweeks in the UK between 2000 and 2001. There were three types of part-time workweeks: standard workday part time, part workday part time and short workweek.

Methodologically, this study has contributed to the on-going reflections and discussions on how costs should be set in OM. We suggest that costs should be defined in accordance with the kind of patterns that researchers expect to see or consider theoretically interesting. For example, we have defined costs on the basis of the transitional frequencies of two states at a given time in this study. Setting the costs on the basis of theoretical concerns will help to emphasize and capture certain patterns effectively. But it does not necessarily imply that the results will be completely changed if a different cost is chosen. In clustering analysis, there are often stable clusters, which exist in the outputs regardless of how the parameters are set. Stable clusters are composed of identical, or almost identical, sequences, which will end up being grouped together with no regard to the costs, since costs are, by definition, only used when sequences are dissimilar. However, the proportion of the stable clusters may vary with the cost, i.e. non-core cases of a cluster are prone to move to another cluster if the algorithm changes. In this case, stressing a certain kind of patterns in OM, by defining the ratio of indel to substitution costs, is tantamount to adjusting the sensitivity of border cases to the stable clusters. When indel costs are low compared with substitution costs, the distance will favour the number of identical events regardless of their location in the sequences. When they are high, similarity of the border cases will be estimated according to their existing positions in the sequences.

In the case of the scheduling of work, it is essential to compare sequences on the basis of their local similarity; otherwise the schedule of events itself will be altered. Furthermore, we employ time varying substitution costs because transition frequencies provide significant empirical and theoretical information on sequence proximity. To apply OM to other research topics, we recommend that users define the costs on the basis of theory and previous findings. When no previous reference is available, researchers may adopt neutral costs close to the Levenshtein I measure so as not to favour either local or remote similarity.

OM is a versatile technique that can easily accommodate two periodicities in its analysis. Although it is possible to apply OM directly to the 672 episodes, it is more appropriate to focus on each of the nested periodicities so that the patterns that are found are clearer and easier to be identified at each stage. The two-stage OM, in the case of nested periodicities, is analogous to noise filtering or seasonal adjustment in time series analysis. The first stage of OM, in which analyses are guided by theory and previous findings, acts as a form of noise filtering.

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