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ScienceDirect

Procedia Computer Science 220 (2023) 283–290

Procedia Computer Science

www.elsevier.com/locate/procedia

The 14th International Conference on Ambient Systems, Networks and Technologies (ANT)
March 15-17, 2023, Leuven, Belgium

Location disaggregation for zone based travel plans

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Abstract

Activity-based models predict locations at TAZ (travel analysis zone) level. Recent research questions about carpooling, ride sharing, vehicle sharing, multi-modality, MaaS, . . . require space resolution at street address level. Pitfalls related to spatial resolution adaptation are identified and a disaggregation method beyond sampling from uniform distributions is presented. Daily travel plans generated by the FEATHERS activity based model for The Netherlands are presented and compared to observations.

Keywords: simulation; agent based modelling; travel plan; activity location disaggregation

1. Introduction - Problem statement

The majority of activity-based models seem to operate at TAZ (travel analysis zone) level and produce OD matrices for further analysis. However, recent research questions require a finer grained spatial resolution. We distinguish between *location* (TAZ level) and *position* (address level) granularity. The latter does require more spatially detailed data and is more resource consuming. A TAZ is a geographical area that is considered to be homogeneous i.e. sufficiently large subsets of the TAZ are characterized by properties that only slightly deviate from each other. TAZs are represented by their centroid and the impedance between centroids is used in location choice models.

Newly emerging research questions cover multimodal trips and short trip segments (legs) e.g. in the MaaS context where transfers are bound to particular services (e.g. shared bike provider, P+R facility). In co-travel analysis (carpooling, ride sharing, . . .) trips for several individuals are combined. Disaggregation of *locations* into *positions* needs careful attention because travel properties of pairs of positions (impedance values) and pairs of sequences of *positions* may be unrelated to the corresponding properties of the containing *locations*. Consider two TAZs T_A and $T_B \neq T_A$. The geometric properties of pairs of positions $p_a \in T_A$ and $p_b \in T_B$ may expose large variety.

The question raises whether trip prediction should be (i) based on *positions* (street addresses) or (ii) based on *locations* (TAZ) and disaggregated in a post-processing stage. Because most schedule (travel plan) predictors operate

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10.1016/j.procs.2023.03.037

at TAZ level this paper focuses on *location disaggregation*. We investigate how the results of TAZ based predictors can be disaggregated to meet requirements for detailed information and use a FEATHERS-based project as an example.

FEATHERS outputs the schedule (daily travel plan) for an individual as a chronologically ordered list of *episodes*. Each episode consists of a *trip* and an *activity execution*. Start time and duration are specified for both the trip and the activity execution. The trip and activity periods for all episodes in a schedule together exactly cover the day without overlapping. A schedule specifies the travel *mode* for each trip and the *activityType* (purpose) for each activity. Other predictors deliver results structured in a similar way.

2. Literature overview

Few models predict travel at street address (facility) level. Most papers operating at TAZ level do not discuss the properties of the zoning in terms of geographical area, number of inhabitants or economic and mobility parameters. This may be due to the availability of only a single dataset at a particular level of spatial detail (e.g. statistical sectors).

2.1. Street address based travel predictors

SACSIM [7, 8] is an activity based model using a temporal resolution of 30[min] and spatial resolution of parcel level for the predicted episodes. Work and school location are simulated for each individual. Hence, persons are assigned a parcel (street address) *before* the travel prediction starts. For work, school and primary tour destination locations, first the TAZ is sampled and then the parcel. Intermediate destinations are sampled in a similar way but more contextual constraints do apply in that case.

Schedule prediction (including adaptation) and schedule execution are simulated in an integrated way by ADAPTS and TRANSIMS [9, 10]; this requires position information to be exchanged between the tools.

SimMobility consists of a long term (LT) simulator, a mid term (MT) simulator which contains a *pre-day* activity based predictor of daily schedules and a short term (ST) simulator which simulates actual movements on the road [2]. The SimMobilityST model receives trip-chains and activity-schedules from SimMobilityMT as inputs and can alter these by rerouting and activity timing adaptation. The spatial resolution for activity locations is the building postcode [12]. This is a 6-digit postal code made up of the sector code (two digits) and the delivery point (4 digits). [1]

Setup of a MATSim model for Baoding (China) is discussed in [18]. The modeled universe is very small. All locations for shopping, leisure, work, education and home are modeled individually in an activity-based schedule predictor which directly exports street addresses. However, the experiment covers an unrealistically small toy model and the design may suffer from combinatorial explosion.

2.2. TAZ based travel predictors

[15] uses the *Kutter model* (Berliner PersonenverkehrsModell) to generate MATSim plans. The Kutter model provides activity chains defining tours in which locations are TAZs and where activity type and mode are specified.

[14] discusses travel demand modeling for Berlin using both a macroscopic model (VISUM) and a microscopic model (MATSim). Data are extracted from an household travel survey (HTS) specifying the home location at statistical zone level along with an activity chain including location, travel start/end times, mode and personal attributes. In order to generate daily travel plans for MATSim, activity locations need to be determined. Home locations are distributed inside the zones according to additional land use information on block level detail. The paper does not mention details about disaggregation.

[20] describes an experiment that uses daily activity plans generated by CEMDAP based on parameters estimated for Los Angeles (the '*estimation context*'), transforms these into plans for Berlin inhabitants ('*application context*') and calibrates the model using CADYTS and traffic counts for the Berlin region. The experiment aims to show that parameters for the entire daily plan can be determined in this way. The synthetic population is generated starting from Berlin data. Each working and/or studying agent is assigned several potential work/university locations based on a

[1] https://en.wikipedia.org/wiki/Postal_codes_in_Singapore

given OD matrix. As a consequence, each such agent can select between plans having different locations. CADYTS is used to force agents to select plans consistent with the given traffic counts. The neighbourhood where the work/school is located in the zone (extracted from the OD matrix) is sampled at random. CEMDAP is executed: it predicts the TAZ for other activities (i.e. different from home, work, school). A random location again is sampled in the TAZ. The papers do not mention details about position sampling.

[13] describes a travel demand and MATSim based assignment model. Home and mandatory activities locations are assigned first. Locations for discretionary activities are assigned at TAZ level based on travel impedance (distance) and attraction. In a subsequent step microscopic coordinates in the TAZ are assigned; details about position sampling are not provided.

Albatross [3] (covering The Netherlands) and the decision tree based FEATHERS_0 described in [6] (covering Flanders, Belgium) predict travel between TAZs. FEATHERS_0 has been applied to the Flemish area of $13,625[km^2]$ using a statistical sectors (approximately 10000) [4, 5] and at a more coarse level using nearly 2400 zones. The recent FEATHERS_4 version predicts travel demand between TAZs using discrete choice modeling. It has been applied to The Netherlands using 7700 TAZs [11]. Both models use impedance matrices for trip distance and duration between TAZs. The matrices have been pre-computed on a loaded network by skimming after traffic assignment.

[1] builds a MATSim model for Flanders starting from FEATHERS_0 predictions and using the CRAB database of Flemish addresses[2]. Each apartment in a building has its own address. The building type (purpose, function) however is not specified in the CRAB database. First, each household is assigned an address drawn from the set of addresses in the TAZ containing the household home location. This is done by means of sampling from a uniform distribution. Addresses that have not been assigned as home addresses are used as '*reusable*' (shared) addresses for shops, schools, companies, etc.

[19] focuses on methodological aspects that need attention when integrating the daily schedule predictor FEATHERS_0 with MATSim. Address disaggregation is done by sampling from the CRAB database using a uniform distribution.

TASHA is an activity based model of the *computational process* type. It is able to handle ride sharing among members of a household. One of the development objectives for TASHA is to not require more data than classical 4-step models. [16] states that the activity generation model is based on random draws of activity attributes from 262 observed joint probability distribution functions of frequency, start time and duration. Persons have given home, work and school locations. The locations of *home* and the usual places of *work/school* are given as model inputs. The activity location choice for other activities is based on a series of entropy models. In TASHA an activity location is specified only to the level of a zone (TAZ). TASHA uses euclidean distance between TAZ centroids [17] as trip distance.

3. Datasets for Location (TAZ) to position (address) disaggregation

3.1. Benelux Address Databases

The Dutch BAG database[3] assigns a set of functional labels to each address. Hence, an address can be mono- or multi-functional. This obviously allows to achieve accurate disaggregated results. In contrast, for Flanders, the CRAB database[4] provides addresses and coordinates for all known buildings. It does not provide functional information about the building. Hence, one needs to assume that each building can serve any purpose.

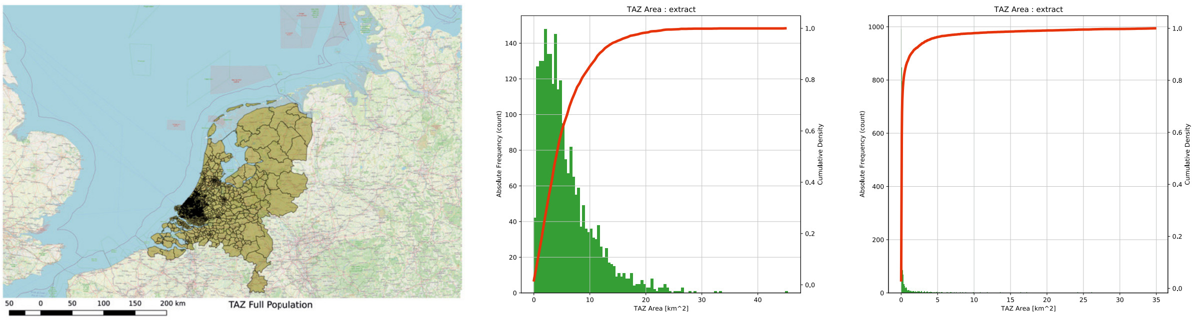
3.2. Benelux TAZ

The problem to be solved is exemplified by considering the application of FEATHERS_4 in The Netherlands. Some of the considerations are FEATHERS specific, some emerge from the available data and others do apply in general. The UTN2 project aimed to predict travel demand for the MRDH (Metropolitan area Rotterdam - Den Haag). The study area is approximated by dense area in Figure 1a. Inhabitants living in the TAZs surrounding the MRDH study

[2] https://overheid.vlaanderen.be/informatie-vlaanderen/producten-diensten/centraal-referentieadressenbestand-crab
[3] https://business.gov.nl/regulation/addresses-and-buildings-key-geo-register/
[4] https://overheid.vlaanderen.be/informatie-vlaanderen/producten-diensten/centraal-referentieadressenbestand-crab

area have been selected for schedule prediction by FEATHERS_4. Note that the selected individuals were able to travel to all TAZs shown in Figure 1a. An additional FEATHERS_4 prediction for the complete population has been executed to produce the results shown in this paper. The zoning is heterogeneous with respect to TAZ size.

Figure 1b shows the distribution of the TAZ area [km^2] for Flanders (homogeneous in size).



(a) TAZ zoning covering the complete country.

(b) TAZ Area distribution for Flanders.

(c) TAZ Area distribution for the simulated Dutch region in the UTN2 project (Rotterdam - Den Haag).

Fig. 1: TAZ area distributions

Figure 1c shows the distribution of the TAZ area [km^2] for the region for which the inhabitants have been simulated to estimate travel demand in the MRDH region. The histogram can barely be seen in Figure 1c since it mainly consists of a sharp peak at the left.. The subdivision for the whole country of The Netherlands shown in Figure 1a has 106 TAZs for which the area is between 50 and 1685 [km^2].

4. Problems - Challenges

1. **Interzonal trip distance assignment**: FEATHERS reports the distance fetched from OD impedance matrix as the trip distance.

   (a) Consequently, the trip distance (and duration) depends solely on the tuple $\langle z_O, z_D, m, t\rangle$, where z_O is the origin TAZ, z_D is the destination TAZ, m is the travel mode and t is the time-of-day (because impedance matrices are used for morning peak, evening peak, midday and rest of the day).

   (b) The trip distance (duration) mentioned in the schedules have been determined by using the TAZ centroid. Actual building (facility) locations have been ignored. The impedance between two TAZs is given by a single numeric value (as opposed to a distribution).

   It is common to first predict tours in a schedule followed by subtours. Location choice follows the prediction of the activity sequence in the (sub)tour. The final result reports interzonal distances. Therefore, the schedule *activity sequence* can be trusted to deviate less from reality than the *reported distances* (and hence episode duration values).

2. **Intrazonal trip distance assignment**: Intrazonal trips require special handling by tools that rely on impedance matrices. For FEATHERS two cases are considered:

   (a) The Flemish FEATHERS_0 model uses a TAZ subdivision that is quite homogeneous. The distribution for the TAZ area is given in Figure 1b. For each intrazonal trip in the Flemish model, FEATHERS_0 specifies `distance = 0` [km] and `duration = 5` [min]. The trip duration does not depend on the TAZ.

   (b) In the UTN2 model for MRDH (The Netherlands) diagonal elements in the impedance matrices specify non-zero distance (duration) values. The values are TAZ-specific and are related to the TAZ size. These values are used for *all* intrazonal trips by FEATHERS_4 in the TAZ. The zoning is shown in Figure 1a.

3. **Subtour information loss**: If, according to a the travel plan (generated by a TAZ-level activity-based schedule predictor), a particular TAZ is visited multiple times, it is unknown whether or not the same address is visited. *Home* and *work* locations are special cases because one can assume they are unique for the individual.

   Since locations are specified by TAZ number, subtours in general cannot be reconstructed from the schedule (except for *home* and *work*) unless *tour identifiers* are included. This does not constitute a problem if the predicted schedules are used to produce aggregated results only (e.g. OD matrices) but it constitutes lack of information for the location disaggregation process.

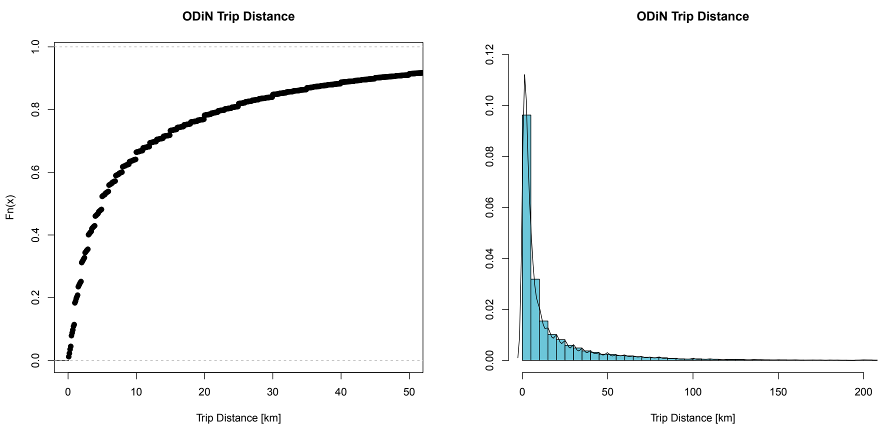
   As an example, *bring-get* activities need attention. The sequence `(H - BG - W - BG - H)` may represent the common pattern (i) home, (ii) drop off children at school, (iii) work, (iv) pick up children from school, (v) home. However different activity sequences are probable too.

4. **Large zone problem**: A zoning system is said to suffer from the *large zone problem* if and only if the fraction of intrazonal trips is too large.

   Definition 4.1 (*large zone problem*). *A TAZ is said to suffer from the* large zone problem *if and only if its radius is larger than the length of a predefined part α of the observed trips i.e. if and only if $Prob(d \leq \rho) = F_p(\rho) \geq \alpha$*

   The maximal radius to avoid the *large zone problem* then is given by $\rho_{max} = F_p^{-1}(\alpha)$ The value $\alpha = 0.33$ is proposed (at most $1/3$ of the trips should be intrazonal). Based on Figure 2a the radius shall be at most $3[km]$. Note that the condition is required to hold for each travel purpose p since exactly one TAZ subdivision is used.

   The trip distance data from ODiN (Dutch travel behaviour research) https://www.cbs.nl/nl-nl/longread/rapportages/2022/onderweg-in-nederland–odin—2018-2020 have been used to estimate parameters for Pareto, gamma and log-normal distributions using R. However, applying the *Cramer - von Mises* criterion indicates that the observed sample is not consistent with the estimated distributions. Hence, we can only rely on the empirical CDF shown in Figure 2a.



(a) Empirical cumulative probability distribution.

(b) Relative frequency histogram and density function.

Fig. 2: Trip distance distribution extracted from ODiN.

5. **Trip chaining and the large zone problem**: For a TAZ τ suffering from the *large zone problem* (see item 4) the majority of trips starting in τ may also end in the τ. In particular, if the home location of an individual is contained in a large TAZ there is a high probability that all activities are predicted to take place in the *home* TAZ. The literature does not mention how to determine properties of intrazonal trips (which may mean they are always assumed to be short). If a very small set of distance (duration) values (i.e. exactly one value for each travel mode) is used for all intrazonal trips in a TAZ, distances between consecutive locations within a TAZ are predicted to be the same (see item 2) which is unrealistic in large TAZs.

6. **TAZ Size Heterogeneity Problem**: The *TAZ size heterogeneity* problem occurs if and only if the fraction of individuals living in a large TAZ exceeds a given threshold. Some of the problems mentioned above apply to regions covered by large zones only. Resulting trip property distributions (e.g. duration) may widely vary between regions covered by large and small zones.

5. Proposed disaggregation method

Stable locations (*home*, *work*, *school*) are assigned a *position* first. This assignment remains fixed during the remainder of the procedure. *Unstable* (volatile) locations may be disaggregated using one of the following techniques.

1. Independent Location Sampling: for each activity, a position is sampled (using a uniform distribution) from the set of appropriate addresses in the TAZ specified in the schedule. The method may lead to unrealistic results due to the *large zone problem* and due to the positions independence.
2. Trip Distance Sampling: a travel purpose and mode specific trip distance can be sampled from observed distributions or inherited from the predicted schedule. In this way each trip can be assigned a decent distance which limits the choice sets for *unstable* locations. Once the home address is fixed, it restricts the chain of addresses that can be visited using given trip distances. Unstable locations cannot be handled independently because in the end, the home-based tour must have a decent total distance which may require computationally expensive backtracking.
3. Consolidated Schedule Sampling: a disaggregation is determined by sampling the position for each *unstable* location. The travel duration is computed for each trip. This is repeated several times and the case delivering the minimum total travel duration is kept. This is based on the idea that people try to minimize travel time.

Note that, for any option, the disaggregation result depends on the order in which individuals are processed because *home* addresses are assigned by random sampling but cannot be shared.

The option mentioned in item 3 was chosen. The number of trials needs to be determined carefully in order to avoid finding always the minimum travel duration. Assume a tour T (possibly containing sub-tours) containing N_V events of *volatile* activity types. For the j-th such event $N_{V,j}$ positions are available. Let S^T denote the set of alternatives for tour T. The number of alternatives then is $M = |S^T| = \prod_{j \in [1,N_V]} N_{V,j}$

Sampling an alternative means sampling a position for each unstable location in the tour. A set $\overline{S}^T \subseteq S^T$ will be drawn by sampling with replacement. Then $N = |\overline{S}^T| \leq M$. Each element $e_i \in S^T$ (schedule) has an attribute $A(e_i)$ (e.g. total travel duration). Assume that the $a_i = A(e_i)$ values are kept in an ordered set. The probability to find at least one of the k smallest a_i values occurring in S^T in the sample $\overline{S}^T$ is given by

$$1 - \prod_{i=1}^{i=k} \Big(1 - P(a_i)\Big) = 1 - \prod_{i=1}^{i=k} \Big(1 - \frac{N}{M} \cdot (1 - \frac{i}{M})^{N-1}\Big) \tag{1}$$

We require $N \leq \beta \cdot M$ with $\beta = 0.5$ by configuration. Numerical example for the probability that at least one value from the subset of smallest values in S^T is included in $\overline{S}^T$: for $M = 15000$ and $N = 300$ the probability to sample a value from the 2% smallest ones in the population (i.e. one of the $0.02 \cdot 15000 = 300$ smallest ones) equals 0.629.

For each pair $\langle$`tazId,activType`$\rangle$ an address sampler is provided managing the set of appropriate addresses based on the *address purpose* labels. An address in a TAZ can belong to several sets since it may have multiple purposes. Sampling is either *with replacement* (for *shared* addresses) of without replacement (for *private* addresses). *Overloading* (assigning an address multiple times) of private addresses is supported in order to overcome (unavoidable) inconsistencies in public datasets. It is reported on the log in order to support data consistency checks.

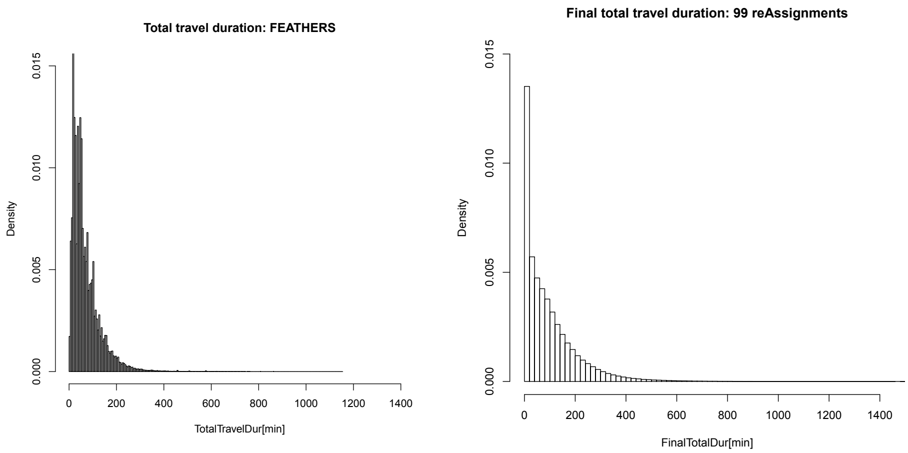
In order to evaluate the effect of the number of trials, random number generation is so that alternatives for a schedule differ solely in the positions for unstable locations. Positions for stable locations and speed values are sampled exactly once and from dedicated random number generators.

6. Results

Comparison between Figures 3a and 3b shows an excess of disaggregated schedules having either a lower or higher total travel duration than the FEATHERS prediction. This is because the proposed method replaces the single *centroid based distance* between TAZs used in FEATHERS for each trip by a distribution of distances between positions.

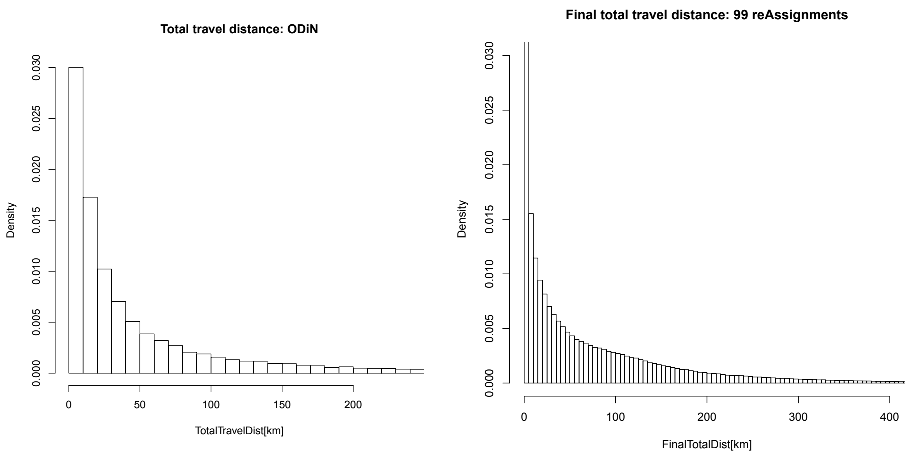
On the other hand, Figure 4 shows that the distance distribution is similar to the one derived from ODiN which was not used in the prediction process. This shows that the proposed method does not suffer from the *large zone problem*.

In an alternative method, the unstable location reassignment probability has been made dependent on the number of available candidates. Instead of specifying the number of *schedule variants* N_s, the number of *position samples* N_p was specified and unstable locations having more candidates have been reassigned more often. The resulting distributions were different but nearly indistinguishable from the ones produced by the original method.



(a) FEATHERS_4 predictions (b) After disaggregation using 99 reassignments.

Fig. 3: Distributions for total travel duration in schedules.



(a) ODiN observations (b) After disaggregation using 99 reassignments.

Fig. 4: Distributions for total travel duration in schedules.

Individuals living in small and large TAZs have been considered separately. Experiments show that mean and standard deviation for travel distance and duration converge to slightly different values for the two sub-populations. This may be caused by the simplistic assignment of work addresses independent from home addresses.

7. Conclusion - Future research

Rough validation showed that the proposed technique leads to decent results. This is to be confirmed by statistical significance testing for distributions similarity. The number of required reassignments needs to be rigorously investigated: experiments using $N = 9$, 99, 199, 299, 399, 1999 and 19999 suggest that 99 reassignments are sufficient to reach stable distributions for the Dutch case.

Acknowledgements

The UTN2 project provided the input (FEATHERS_4 predicted schedules) for this study.

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