Temporal transferability of a microsimulation activity-based model: An application in Chile

Víctor Allendes[1], Juan Antonio Carrasco[1,2,*], Eric J. Miller[3,4], James Vaughan[4]

1: Departamento de Ingeniería Civil, Universidad de Concepción, Chile
2: Instituto de Sistemas Complejos de Ingeniería, Chile
3: Department of Civil & Mineral Engineering, University of Toronto, Canada
4: University of Toronto Transportation Research Institute
*: Corresponding author

Abstract

Urban transport policies in the Global South use mostly traditional trip-based models to replicate and predict individuals' travel in different urban contexts. Given their aggregate nature, they are limited when applied at a more disaggregated scale, contrasting with activity-based models, which have been used mainly in the Global North. In addition, there is a critical need to add empirical evidence to understand the models' temporal transferability, which involves their capability to predict future travel behavior based on estimations with data collected in the present. This paper reports on the replicability and temporal transferability of an activity-based model in Chile. The objective is to understand the challenges of applying these models in these contexts for usefulness in policies. The model used in this paper is TASHA (Travel Activity Scheduler Household Agent), which acts in a more disaggregated context than traditional models. This evaluation consists of two stages: (a) replication and prediction of activities and trips for a base year, (b) temporal transferability of previously estimated parameters to a future year. The exercise provides valuable proof of principle of several arguments about the advantages of activity-based models such as TASHA. First, the study shows the model's ability to capture current and future behavior despite data and context limitations. Second, the model supports the analysis of activities in addition to trips, providing a more in-depth assessment of travel behavior. Finally, and more importantly, the focus on activities, such as end times, emphasizes the critical need to incorporate more explicitly policies beyond those traditionally.

1. Introduction

As in other parts of the world, urban transport planning agencies in Chile and the Global South use travel demand models to assess the impact of interventions in the transportation system (Ortúzar and Willumsen, 2011). Most of these models follow a trip-based paradigm, which assumes trips as the central unit of analysis, usually using econometric-based frameworks. Despite their usefulness, there is an increasing interest in applying more sophisticated methods to assess the complexity of travel behavior in urban areas, acknowledging that trips are motivated by the need to perform activities (Axhausen and Gärling, 2007). With this argument, activity-based models focus their unit of analysis on activities rather than trips, allowing the analysts to dig into more complex behavior such as trip chaining, personal interaction, and 24 hour and fine time scales (Rasouli and Timmermans, 2013). These arguments have fostered several applications in the previous decade, transforming activity-based models into a vital tool to assist planning agencies in forecasting the impact of transport-related interventions in urban areas. Although most of these models started in the developed world, there is an increasing interest in applying and assessing their capabilities in other world regions, as agent-based model applications in the Global South remain scarce. Although these activity-based models were introduced two decades ago as an alternative to four-stage, trip-based models, the current state of practice differs among different countries, remaining significant gaps in their applicability (Rasouli and Timmermans, 2013).

One critical aspect of fostering more activity-based applications involves understanding the extend to which they accurately predict future travel behavior based on models estimated with data collected in the present. In other words, there is a need to provide evidence about the model's temporal transferability, studying their ability to replicate and predict people's current and future behavior, respectively. Despite previous efforts on investigating these issues both for trip-based (Badoe and Miller, 1995; Fox *et al*., 2014) and activity-based models (e.g., Roorda *et al*., 2008), empirical applications are still very limited in the literature.

With this motivation in mind, the paper's objective is to assess the temporal transferability of an activity-based model within a Global South context. The model used in this paper is TASHA (Travel Activity Scheduler Household Agent), developed by Miller and Roorda (2003). A significant reason for this choice is that TASHA requires standard travel survey data for its application and that most of its previous applications have been in the developed world. The case study is Temuco, a medium-sized city located in Chile. The research consists of two stages. The first stage involves studying the replication of activities and trips in Temuco for the base year 2002. The second stage consists of predicting activities and trips for the same urban area in 2013, using the model calibrated with 2002 data.

This paper contributes to this literature in two ways. First, TASHA has only been applied in the Global North, except in Asunción, Paraguay (UTTRI, 2017), but not reported as systematically as the application presented in this paper. Second, and more importantly, the urban transport situation in the Global South is very different compared to previous applications from the developed world. Global South cities such as Temuco have a higher share of public transport and a rapid car ownership growth. At the same time, unlike Toronto or other similar cities, urban areas such as Temuco have lax land-use regulations and thus rapid changes in activity locations and urban growth. These aspects may constitute a challenge to forecast activity-travel for models such as TASHA.

The article is structured as follows. Following this introduction, the second part presents the theoretical background of the empirical exercise. After briefly discussing trip and activity-based models, that section defines temporal transferability more formally. The end of the second section presents the essential characteristics of TASHA and past efforts to validate that model. The third section discusses the data and methodology used in the application. The fourth section presents the model's ability to replicate the base year and the model's temporal transferability capabilities in the case of study. The last section discusses the main conclusions and potential future work.

2. Theoretical background

2.1 Trip and Activity-Based Models

The literature on traditional four-stage trip models is extensive, with a history of more than sixty years. Most of these models are trip-based, depend heavily on random utility maximization, and focus on specific travel purposes and travel-based assumptions (Ortúzar & Willumsen, 2011). The main advantage of these models is their simplicity in use and understanding and their relatively good performance to forecast future demand (Ortúzar & Willumsen, 2011). In Chile, transport projects use the trip-based models ESTRAUS (7.6 version, SECTRA) and VIVALDI (7.6 version, SECTRA). ESTRAUS predicts the supply and demand equilibria simultaneously and is well-suited for application in large, congested cities. In contrast, VIVALDI is a sequential algorithm for predicting the system's performance that applies only to medium-sized cities. Siegel *et al.* (2006) give detailed analyses and comparisons between the sequential procedure model (VIVALDI) and the combined network equilibrium model (ESTRAUS).

Although these traditional models have been helpful for the country's transport infrastructure assessment, they have limitations when describing people's complex behavior. In fact, given their aggregate nature, trip-based models are limited when applied to more complex disaggregated policy questions. Since the fundamental unit of analysis is the trip itself, these models have relevant limitations in representing the activities and schedules people need and want to carry out within their trip tours. Several other limitations of traditional models discussed in the past include their static segmentation, their lack of intrahousehold consideration, their limited representation of the time of the day, their inability to incorporate scheduling constraints, and the competition for the use of household cars (Bifulco *et al*., 2010; Moeckel *et al*., 2020).

Activity-based models overcome such limitations as they consider travel as a demand derived from the activities individuals and households wish to engage in, including intra- and inter-home relationships in the modeling process. Davidson *et al.* (2007) enumerate their main advantages over traditional models:

- Explicit modeling of intra-household interactions and joint travel, which is of crucial importance for realistically modeling individual decisions within a household
- Enhanced temporal resolution with an explicit tracing of available time windows for activity generation and scheduling of the tour
- Considering individual trips and activity chains rather than unrelated trips.

These models have been under development since the 1970s to improve travel estimation and overcome trip-based models' limitations. Many countries have currently developed this tool to replicate and predict travel behavior in their urban areas. Examples include FAMOS (Pendyala *et al.*, 2005), SACSIM (Bradley *et al.*, 2010), the Boston Model (Bowman and Ben-Akiva, 2000), and the San Francisco model (Jonnalagadda *et al.*, 2001) in the United States; the Jakarta Model in Indonesia (Yagi and Mohammadian, 2009); ALBATROSS (Arentze and Timmermans, 2004) and FEATHERS (Janssens *et al.*, 2007) in The Netherlands; PETRA in Denmark (Fosgerau, 2002); SIMS in Sweden (Algers *et al.*, 1996); the Tel-Aviv model in Israel (Shiftan *et al.*, 2004); and the Thiruvananthapuram model in India (Lekshmi, Landge & Kumar, 2016). The reader can note that most of these applications belong to the Global North.

2.2 Temporal transferability

A useful model requires replicating the current behavioral situation and performing a reasonably good forecast of these impacts of the future. Thus, a critical feature of any model is its *temporal transferability*. Koppelman and Wilmot (1982) define *transfer* as "the application of a model, information, or theory about the behavior developed in one context to describe the corresponding behavior in another context (p. 18)". Then, transferability defines as "the usefulness of the transferred model, information or theory in the next context" (op. cit., p.18). *Model transferability* becomes the effort of "assessing the ability of models developed in one context to explain behavior in another context, under the assumption that the underlying behavioral theory on which the model is based is equally applicable in the two contexts" (Fox et al., 2014: 43). Thus, *temporal transferability* can be defined as "the application of models developed using data collected at one point in time at another point in time" (op. cit., p.43).

Although temporal transferability has been a concern from the early times on travel demand development (e.g., Parody, 1977), Fox and Hess (2010) show the relatively low number of current empirical studies addressing these issues for travel demand models, arguing that this as a "serious shortcoming the field." Their overview of temporal transferability in mode-destination choice models argues about the need to study long-term horizons, acknowledging this requires data consistently gathered throughout the years (Fox and Hess, 2010). A follow-up work (Fox et al., 2014) shows the need to concentrate on model specification and the mixed results obtained when assessing the different travel behavior dimensions. Finally, temporal transferability on activity-based models is even scarcer, with notable efforts on TASHA (Roorda et al., 2008; Yasmin *et al*., 2015; 2017b), discussed in the following subsection.

2.3 Travel Activity Scheduler Household Agents: TASHA

This paper applies TASHA (Travel Activity Scheduler Household Agent), which is an activity-based model developed by Miller & Roorda (2003), and subsequently validated for the Greater Toronto-Hamilton Area (GTHA) in Canada (Miller *et al.*, 2016; Roorda, Miller, & Habib, 2008). This model uses conventional trip diary data and, therefore, can be applied anywhere such data are available, although special activity-based surveys could be used as well if available. TASHA's procedure for activity modeling is event-driven, with a bottom-up approach. This method captures dynamic behavior as the model continuously changes in response to new opportunities and restrictions for individuals before executing their schedule. Therefore, the people's agenda is built by taking activity episodes from the project agenda to execute afterward.

TASHA's conceptual representation involves an activity generation model based on random draws of activity attributes, taken from the observed joint probability distribution functions of frequency, start time, and duration, by activity type. The choice of activity location is based on a series of logit models, except for home and the usual place of study or work, considered exogenous inputs to the model as longer-term decisions. The activity scheduling model uses a rule-based method. The activities are introduced to an individual project agenda and included in a preliminary time sequence with activities that serve the same purpose. As activities are incorporated, conflicts are likely to occur, resulting in the change, rejection, or reduction of the activity duration. The mode choice model is a random utility tour-based model, which incorporates the household-based mode choice and a vehicle assignment process that explicitly searches for shared opportunities within the home. These outputs are used to interact with road and transit assignment models. The model is currently in its fourth version and is in operational use by most transportation planning agencies in the GTHA (Miller *et al.,* 2016; Miller *et al*., 2020).

Roorda *et al*. (2008) used data from travel surveys of 1996 and 2001 for the Greater Toronto (GTA) to study the model's verification and validation, arguing that their results were strong enough to guarantee the consideration of TASHA as an alternative to conventional modeling systems. Another validation study considered a spatial transferability test (Yasmin, Morency, & Roorda, 2015). At an aggregate level of analysis, TASHA provided good results for Montreal Island for all attributes associated with work, school, and home activities, with few exceptions. Although the model performed well, the frequency and start time for the shopping activity presented some differences regarding the two cities' activity durations. The study concluded that TASHA could be transferred to a new context where there is no data available. However, the parameter re-estimation and local activity attribute distribution (frequency, start time, and duration) is a desirable step for successful spatial transferability. A complementary effort by Yasmin, Morency, & Roorda (2017a) focused on the model's spatial transferability in three different levels: macro-level (aggregation of the entire population), meso-level (aggregation by population segments by age group and gender, and by home location), and micro-level (individuals). The validation results at macro and meso-level demonstrated that TASHA could reproduce activity behaviors in that different context, at least for fixed activities (work and school) with a few exceptions.

Complementarily, Yasmin *et al*. (2017b) examined changes in activity generation attributes in ten years in the Greater Montreal Area (GMA), studying how these attributes vary with socio-demographic characteristics. The analysis demonstrates that distributions of the frequency of work, school, shopping, and other activities were significantly different over time. The same happened to the start time and duration distributions. Several reasons caused these effects: An increase of women in the workplace, workers, and children less often return home during lunch hour, people might be shopping more often in the weekends than on weekdays; online shopping might also be another contributing factor in this reduction and an increased travel time due to urban congestion.

3. Data and Methodology

3.1 Data

The case study is Temuco in Chile, a city located 680 km south of Santiago de Chile and inhabited by 410,520 people in the year 2016. This urban area has a monocentric activity system, with most of the jobs, commerce, and schools located downtown; this area involves around 40% of the overall trip attraction during weekdays. In 2013, the car ownership rate was 0.53 per household, with significant differences among income groups. The study from the same year calculated slightly more than 1 million trips per day. Private and public transport had a 35% share each on weekdays, followed by walking, representing around a quarter of the trips.

The dataset employed to assess TASHA's replicability in Temuco corresponds to the city's 2002 trip diary (MIDEPLAN, 2002), which involved 2.3% of Temuco's households (1600 households). The dataset used to study TASHA's temporal transferability is the city's 2013 trip diary (TRASA, 2013), which involved a 4.13% sample of Temuco's households (3500 households). Other studies in the area provided additional information from the city and transportation system characteristics (e.g., CIS, 2006). Although the 2002 sample size is smaller than the 4% recommended in the literature (Ampt and Ortúzar, 2004), this value is in line with similar efforts in other world regions (Habib and El-Assi, 2016). The relationship between sample size and validity is still debatable in the literature as it depends strongly on fieldwork and sampling schemes (Ampt and Ortuzar, 2004; Habib and El-Assi, 2016). However, travel surveys in Chile have a long tradition dating from 1977 (Ortúzar, 2006) and follow the normal state of the practice methods performed in other countries such as Canada, Australia, and the United States (Ampt and Ortuzar, 2004). The 2002 and 2013 surveys in Temuco use a stratified random sampling scheme and usual practice for fieldwork and input procedures for these kinds of efforts.

3.2 Methodology

Figure 1 presents schematically the two-stage methodology developed in this paper. The first stage consists of the data assembly of the 2002 survey, coding the city road and transit networks, and validating the results. The second stage includes assembling the 2013 trip diary, city network coding, and assessing the model's temporal transferability.

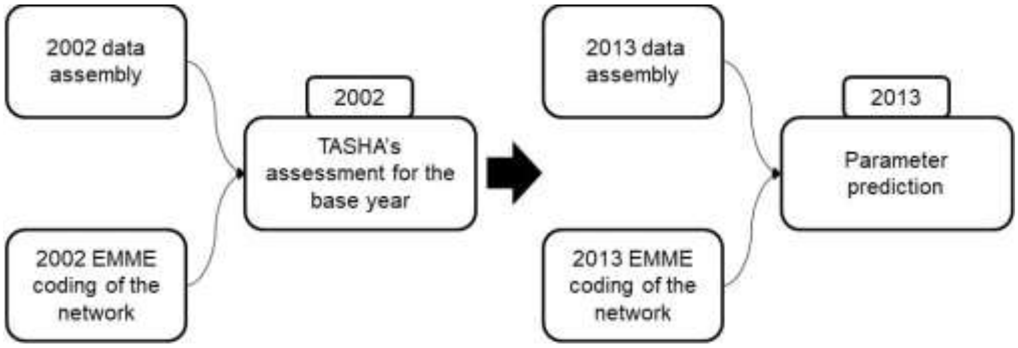

Figure 1. Methodology of the study

The city network was coded for both years in EMME (4.4.3 version, INRO). The survey data includes both individual and household characteristics. The datasets include educational level, occupation, employment status, age, sex, driver's license possession, and residence zone at the individual level. Other information available includes size, number of vehicles, area location, and income level at the household level.

In the first stage, using the initial data extracted and coded, the estimated models include activity generation, Place of Residence / Place of Work (PoRPoW) linkages, and mode choice. Regarding location choice and car and transit assignment, the parameters calibrated for Toronto were directly transferred to Temuco due to data availability issues. After parameter estimation, the final models were calibrated and validated. The calibration involved two types of parameters:

- Activity attributes: A *k*-factor was applied to decrease or increase each activity's frequency, start time, or end time. For example, if the model underestimates work activity frequency, a factor is applied to increase it. Similarly, if the model overestimates school activity start time, a factor will decrease it.
- Mode choice: For this case, two constants were calibrated: a space-time constant and a worker category constant. In the first case, auto driver, rideshare, and car passenger were excluded. For the second case, only the auto driver was excluded. For example, if the model overestimates walk trips between zones 1 and 3 in the AM period, the constant will decrease in value to make this mode less attractive between them. An example for the second case involves when the model underestimates the transit trips of professional workers; in this situation, the constant will increase in value to make these trips more attractive. Unfortunately, the calibration for each socioeconomic level was not feasible since current TASHA specification does not incorporate income as a relevant attribute for the activity distribution, location choice, mode choice, and traffic assignment model.

Finally, the validation process compared the model results and the 2002 trip diary information for different parameters. An R^2 indicator were also calculated to verify the level of statistical fitness of the results for different outcomes.

The second stage studied the model's ability to predict 2013 observed travel using the parameters previously estimated for the 2002 base year. This temporal transferability test involved examining the ability of activity and mode choice parameters calibrated in 2002 to predict 2013 travel behavior. The results were compared with the 2013 observed data using the same criteria as the previous stage. In this case, no parameters were re-estimated; in other words, the activity generation, PoRPoW, and mode choice parameters estimated in the first stage were directly transferred.

4. Results and discussion

The first part of this section presents the results from replicating the 2002 base year activities and trips. Observed and modeled data are compared, including each activity attribute (frequency, start time, and end time); mode splits for each period; trip origin, destination, and distribution; as well as traffic flow. The second part presents the results of the prediction stage using the 2013 dataset.

4.1 Base year replication

4.1.1. Number of activities

The activities defined for Temuco are work (W), study (S), and other (O). Activities labeled as "other" include social and recreational, errands, eating or drinking, health services, shopping, and return home activities. These categories were defined to mimic the original from Toronto. The return home activities are not generated explicitly but are the default activity performed if no other out-of-home activities are generated (Roorda *et al*., 2008). This "other" activities aggregation comes from the Toronto framework used to develop the original TASHA version. A more disaggregated representation of non-work/school activities is not available. The modeling framework can support a more disaggregated set of activity types, but this would require reprogramming the current software, which was not feasible during the current study. Table 1 shows the frequency of activities estimated by the model compared to those observed in the 2002 survey. Overall, the total number of generated activities shows an overestimation of 1.69% relative to the observed. The activity that presents the most significant difference is work, which is overestimated by 2.52%. These differences are like those reported in other applications from TASHA (Miller and Roorda, 2003). Also, the overestimation of work may occur as this purpose has the highest priority among all activities in the scheduling assignment.

Activity	Survey	Model	Difference	Error (%)
W	107430	110138	2708	2.52
S	59523	60605	1082	1.82
O	391771	397421	5650	1.44
Total	558724	568164	9440	1.69

Table 1. Activity frequency.

4.1.2. Activity start and end times

It is important for transport policy analysis purposes to adequately replicate the activities and trips by the hour of the day, represented by their start and end times. Figures 2 to 4 show the probability distribution of weekday activity start times, and Figures 5 to 7 show the distribution of weekday activity end times for work, study, and other.

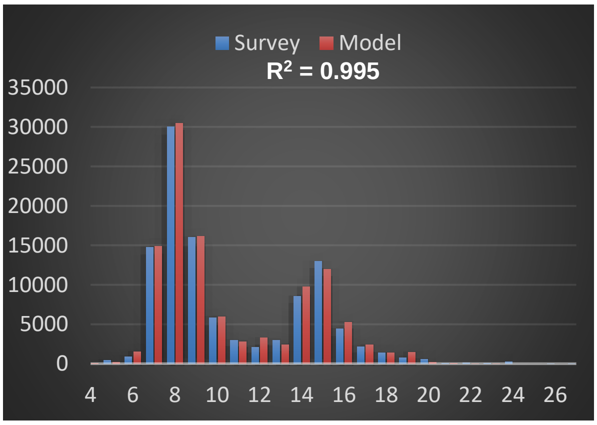

Figure 2. Activity start time distribution for "work"

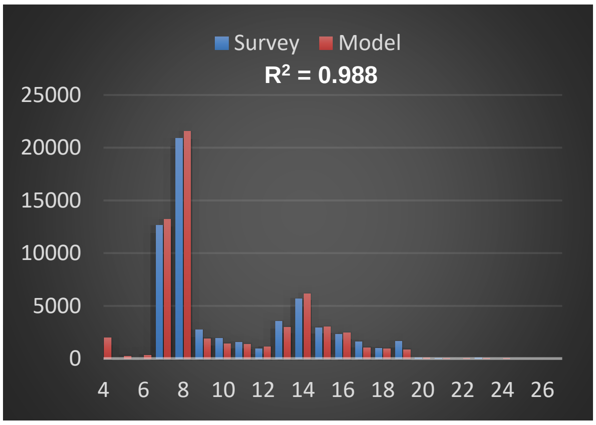

Figure 3. Activity start time distribution for "study"

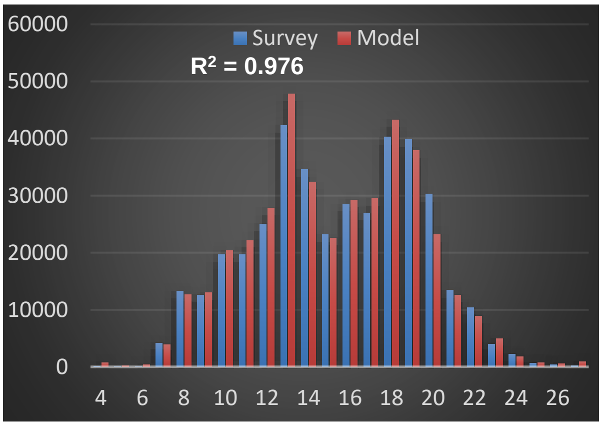

Figure 4. Activity start time distribution for "other"

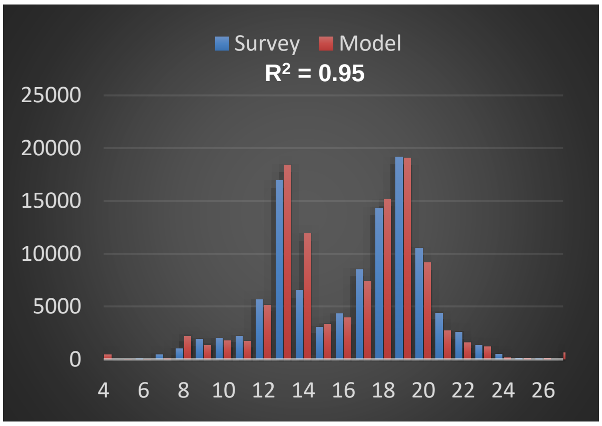

Figure 5. Activity end-time distribution for "work"

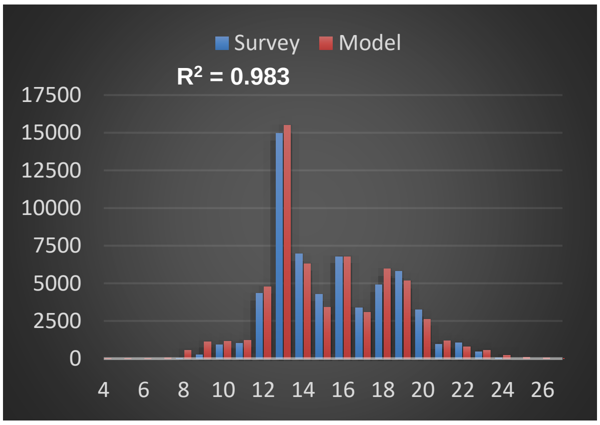

Figure 6. Activity end-time distribution for "study"

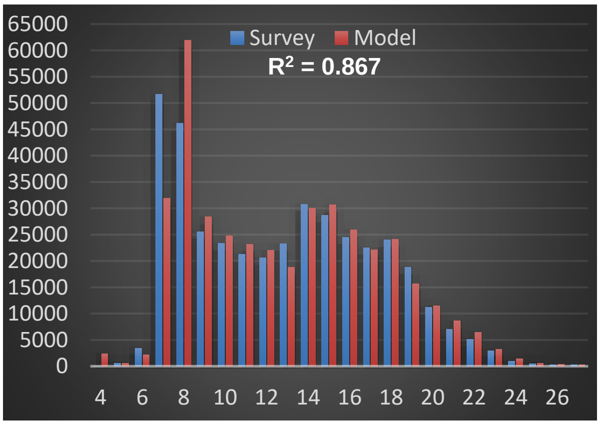

Figure 7. Activity end-time distribution for "other"

Overall, the start time distribution of every activity type has a good fit to the observed data with a few exceptions at the early times. On the other hand, the end times estimation presents certain differences at a more disaggregated level. First, other activities show a 36% underestimation at 7 am, and a 38% overestimation at 8 am. Part of this result may be a consequence of "binning" times into one-hour time slots. In other words, a difference from one to five minutes in an activity episode end time can result in the activity shifting from one bin to another. For example, 4.96% of activities ended from one to five minutes before and after the hour slot. Similarly, 12.1% of activities started from one to five minutes before and after the hour slot for the start time distribution.

4.1.3. Mode choice

In terms of mode choice, the analysis included auto driver (C), auto passenger (P), transit (T), walk (W), and other modes (O). Other modes include bicycle, school bus, rideshare, and carpool, referred to as taxi in this context. The results are categorized by time of the day. Figures 8 to 11 show the mode splits for the morning peak (AM, 7:30 – 9:30), mid-day (MD, 9:30 – 15:30), afternoon peak (PM, 15:30 – 17:45), and evening (EV, 17: 45 – 24:00) periods, respectively. The graphs indicate a clear preference for transit and walk across every period, like the survey data. The EV period shows the highest discrepancy during the day. Yet, overall, the model generates a good fit for the mode splits by period.

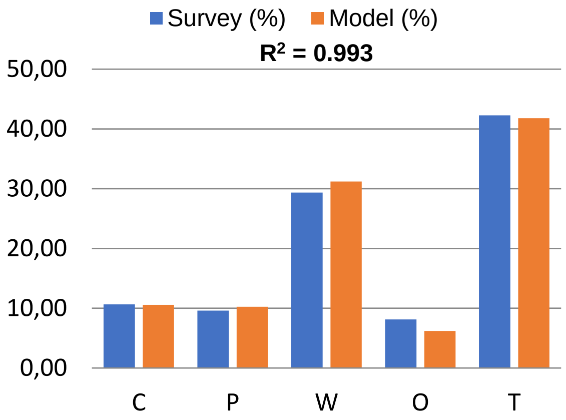

Figure 8. Mode split in AM period

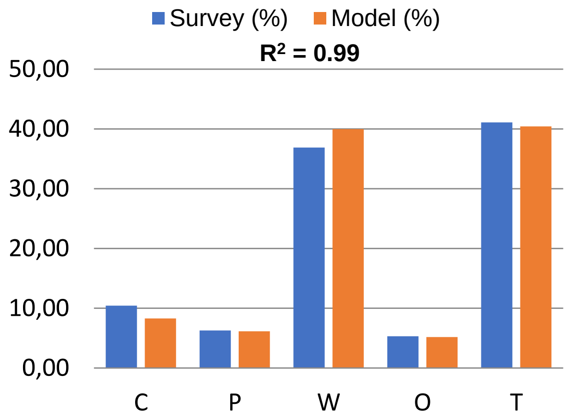

Figure 9. Mode split in MD period

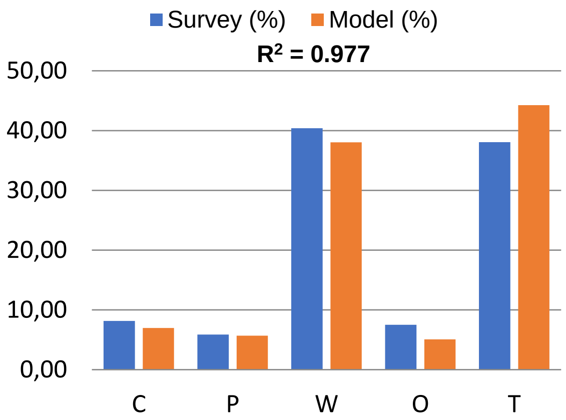

Figure 10. Mode split in PM period

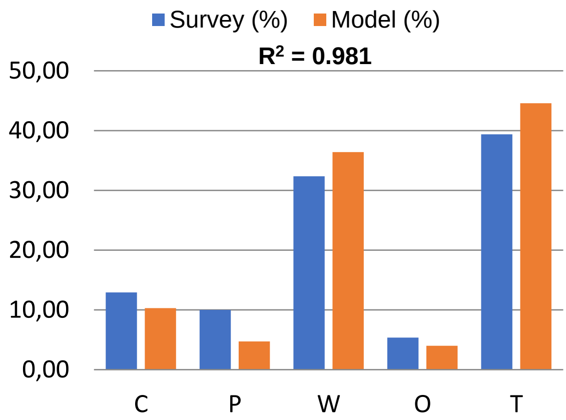

Figure 11. Mode split in EV period

4.1.4. Trips

The origin and destination trip results for the AM period are presented in Figures 12 and 13. Overall, the model underestimated 11% for trip destinations and origins in the AM period and 1% for the total trips. However, some zones present higher discrepancies at a more disaggregated level. For example, the model overestimates trips on 190% at zone 3 and underestimates them on 34% at zone 12.

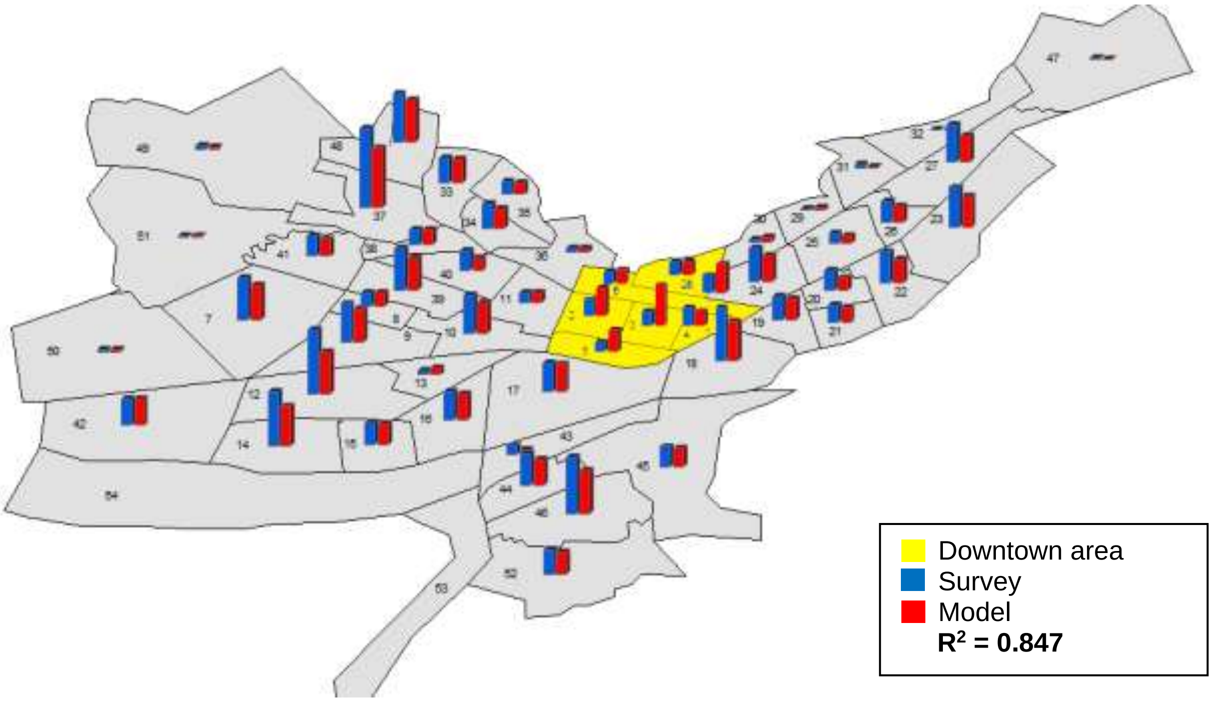

Figure 12. Trip origin AM period.

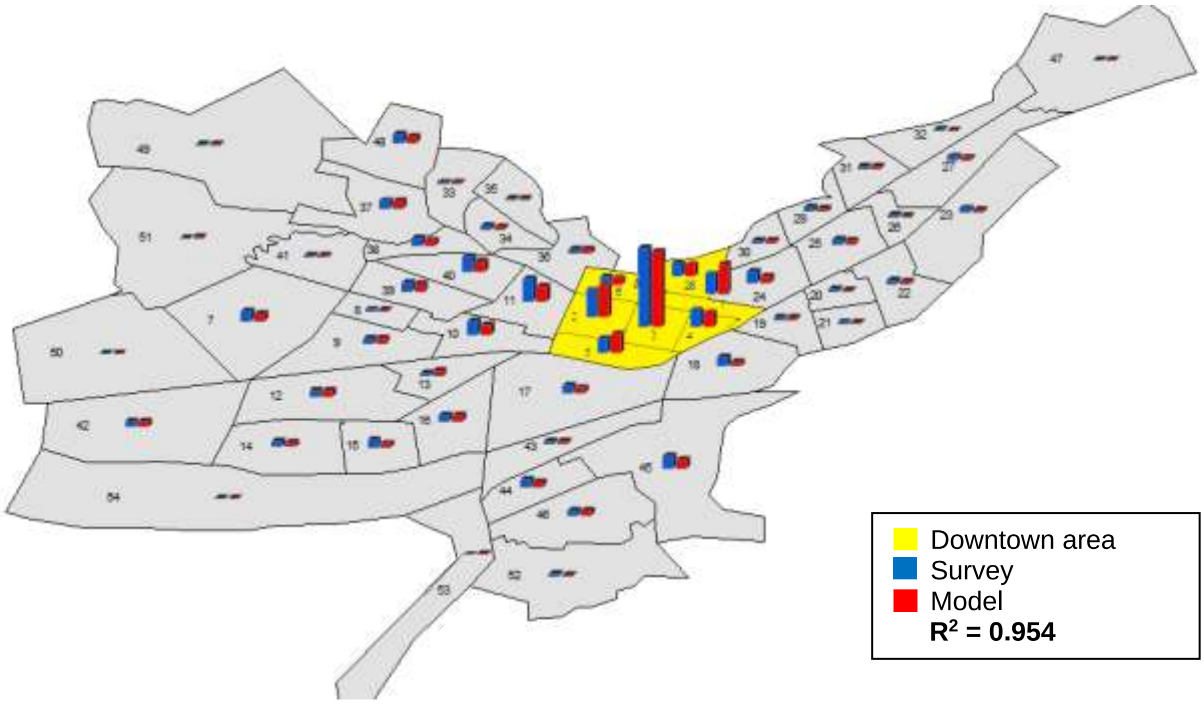

Figure 13. Trip destination AM period.

A complementary perspective on the model's performance involves analyzing the trip distribution relative errors among different macro-zones in Temuco for the AM period. These macrozones are presented in Figure 14, and the results are shown in Table 2. Although the other periods were studied, this trip distribution table represents the most relevant trends regarding this validation process.

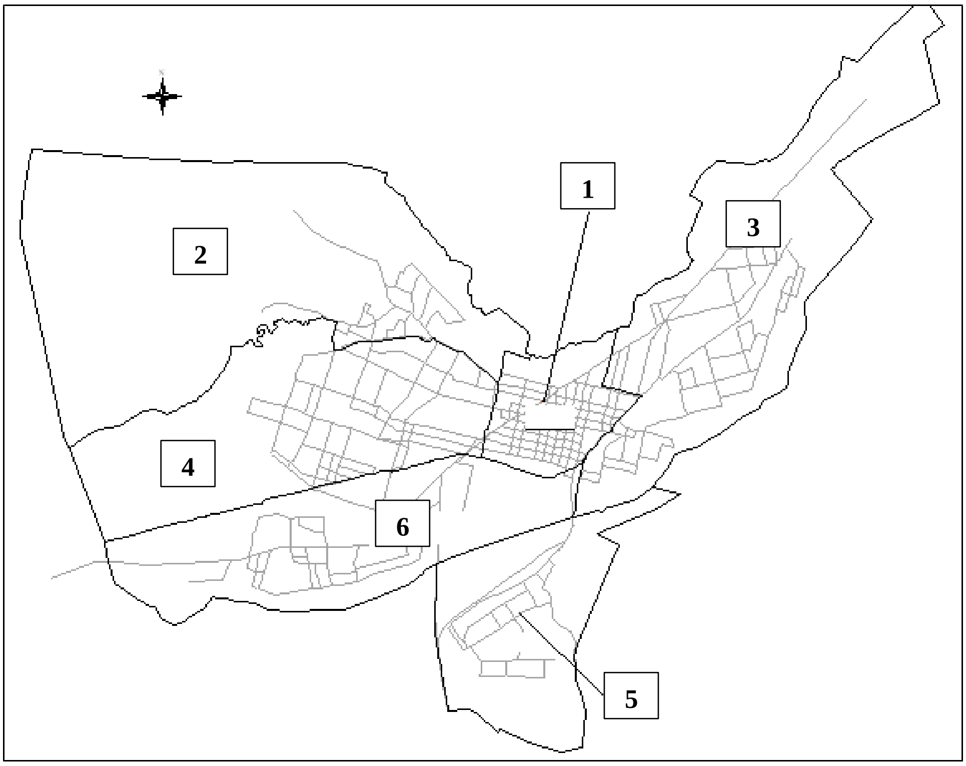

Figure 14. Areas of Temuco.

O/D	1	2	3	4	5	6	TOTAL
1	26.6%	181.8%	59.2%	38.4%	291.6%	578.9%	65.3%
2	22.1%	-41.6%	29.8%	-70.1%	1.7%	12.7%	-14.3%
3	-8.7%	178.1%	-58.1%	2.2%	22.1%	27.5%	-20.8%
4	3.3%	16.1%	-26.2%	-33.2%	-20.3%	-53.5%	-15.6%
5	20.4%	-62.0%	0.9%	-13.3%	-50.0%	-5.7%	-19.7%
6	-3.3%	12.3%	-8.8%	-10.0%	-7.5%	-40.5%	-13.7%
TOTAL	6.0%	-14.2%	-33.5%	-21.8%	-25.1%	-9.5%	-13.3%

Table 2. Relative error of trip distribution on the AM period.

The overall values show an overall underestimation of 13%. However, some OD pairs present very high overestimation values. This result could relate to the Place of Residence / Place of Work model (PoRPoW), representing the linkages between each person's residence and workplace. The workplace location was assumed based on the trip destination with work purposes, As the survey does not explicitly indicate everyone's workplace location. This assumption directly impacts the PoRPoW model calibration process and, thus, it may have generated an important error source.

Vehicle counts, available from the same 2002 data collection effort, were compared with the modeled vehicle flows. These data consist of manually generated counts (PER) and automatic stations (EA) belonging to the AM period. Vehicle turns were excluded from the comparison, given the complexity of incorporating them in the EMME traffic assignment software. The analysis concentrated on the AM period since the survey and this study consistently defined AM from 7:30 to 9:30 in the morning. The adjusted R^2 obtained in the vehicular flow validation was 0.769, a reasonably good value for these studies (CIS, 2006).

4.2 Forecast validation

4.2.1. Number of activities

Table 3 provides a comparison between predicted and observed data for 2013. Overall, the total number of activities predicted has a reasonably good fit, with an overestimation of around 4%. The activity that presents the most significant difference is trip work frequency, where the model gives an overestimation of 14.37% relative to the survey data.

Activity type	Survey	Model	Difference	Error (%)
W	109892	125688	15796	14.37
S	57665	57210	-455	-0.79
O	450456	459578	9122	2.03
Total	618013	642476	24463	3.96

Table 3. Predicted activity frequency.

4.2.2. Activity start and end times

Figures 15 to 17 show the predicted start time distribution for work, study, and other activity, respectively; Figures 18 to 20 present the predicted end-time distributions for these same purposes.

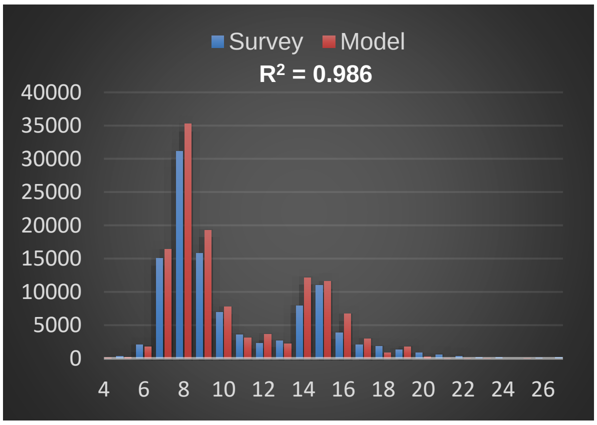

Figure 15. Predicted activity start time distribution for "work"

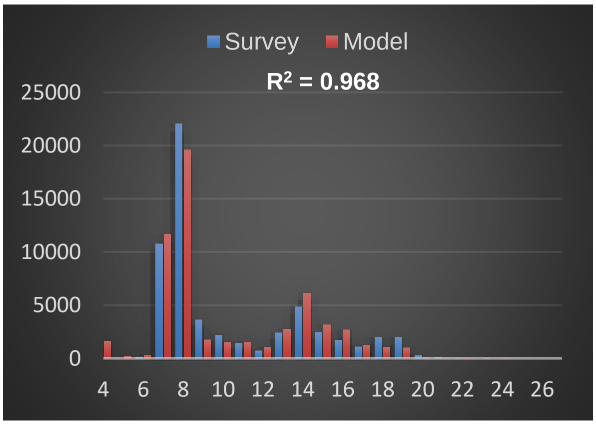

Figure 16. Predicted activity start time distribution for "study"

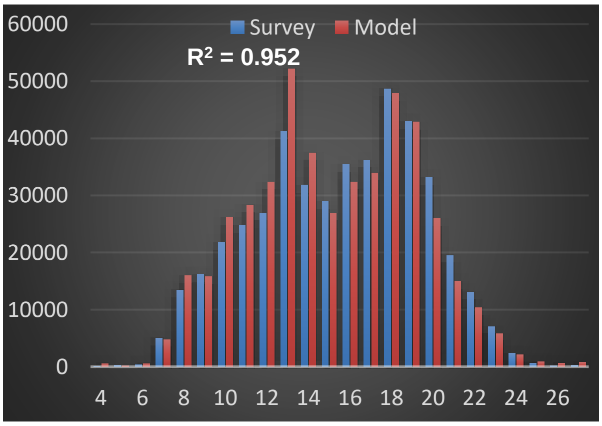

Figure 17. Predicted activity start time distribution for "other".

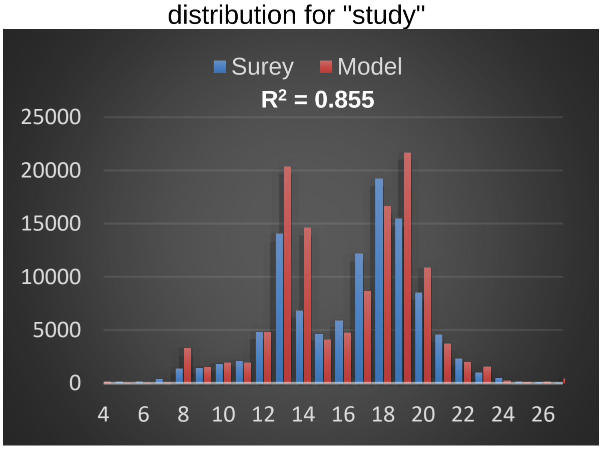

Figure 18. Predicted activity end-time distribution for "work"

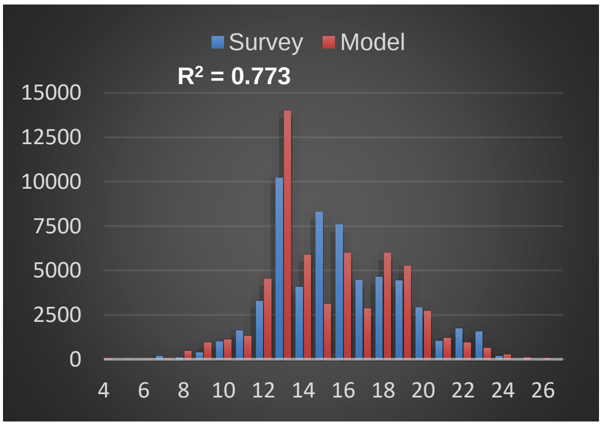

Figure 19. Predicted activity end-time distribution for "study".

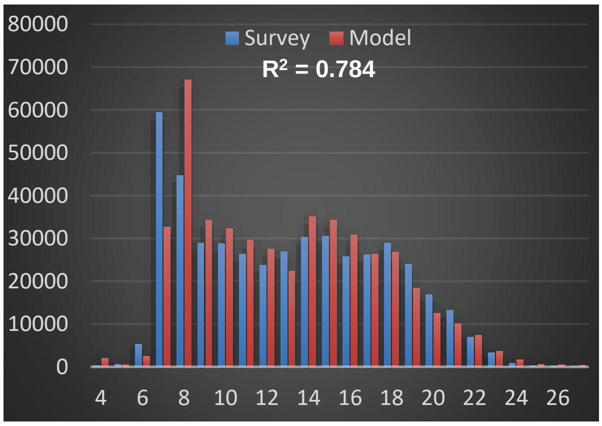

Figure 20. Predicted activity end-time distribution for "other".

The predicted start time distribution shows slightly more errors than the base year estimation. However, in general, the results seem acceptable, given the 10-year time horizon. On the other hand, the predicted end time distribution has a somewhat worse fit in most activities.

To further analyze the possible reasons for some of the above discrepancies, the behavioral changes between both years were explored in greater depth. Work and study activities gathered from the data from both years were compared, considering that these are the most important activities in magnitude. Figures 21 and 22 show the start time distribution rates for work and study from both surveys, and Figures 23 and 24 show the end-time distribution rates for the same activity types.

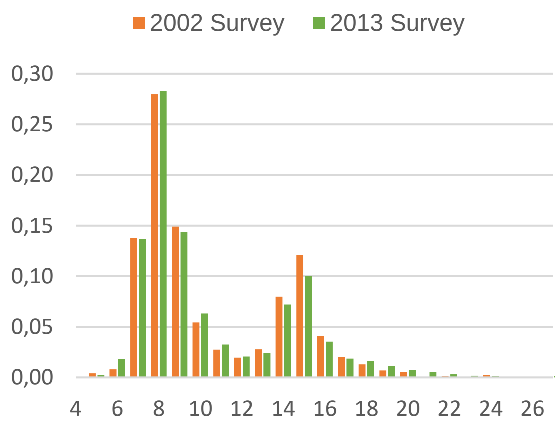

Figure 21. Start time distribution rates of the work activity.

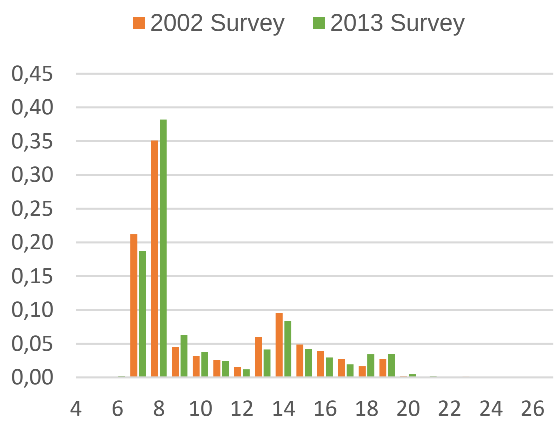

Figure 22. Start time distribution rates of the study activity.

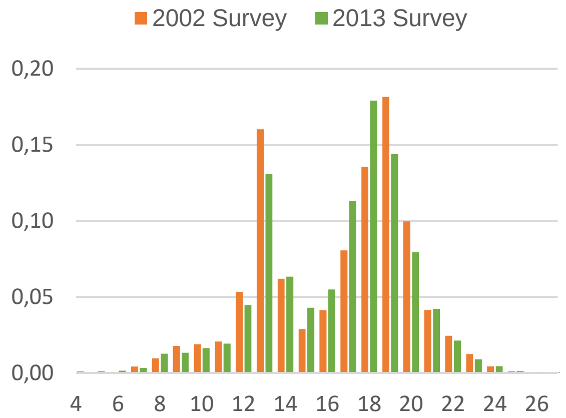

Figure 23. End time distribution rates of the work activity.

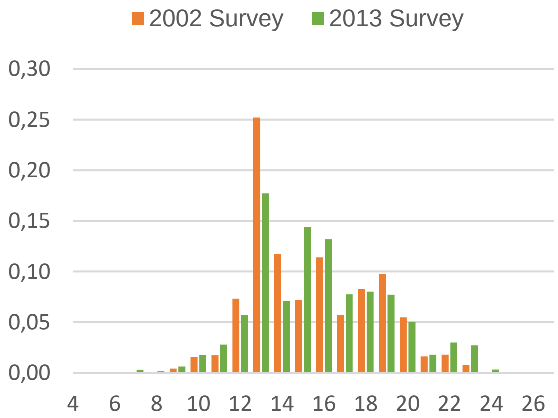

Figure 24. End time distribution rates of the study activity.

The number of workers and the number of students each year were normalized to account for demographic changes. The graphs present differences in the end-time distribution for each activity. For instance, in 2013, fewer workers finished their work activity at 1 pm and 7 pm than in 2002. On the other hand, fewer students ended their school activity at 1 pm and 2 pm, and more students finished at 3 pm and 4 pm. This result directly impacts the other activities since the hours in which the market, home, and "other" types of activities are performed depend heavily on work and study.

Possible reasons for people's behavioral changes are other contextual policies that affected workers and students. Between 2002 and 2013, the weekly work hours changed from 48 hours to 45 hours per week, resulting in more workers finishing their work activities earlier. Also, in 1996, the government changed the schools' hour structure. Initially, school students had only morning classes that ended at 1 or 2 pm; but the government pushed for a full-time school day, implying that activities would finish later, at 3, 4, or 5 pm. This measure was implemented gradually over the years as the schools had few resources to implement it immediately, and in the period of this study, the change was still ongoing. This issue illustrates the model's limitation on handling significant behavioral changes in the population due to non-transport policies.

4.2.3. Mode choice

Regarding mode choice predictions, Figures 25 to 28 show mode splits for the AM, MD, PM, and EV periods, respectively, for 2002 and 2013. As in the 2002 base case, there is an overestimation of transit and an underestimation of car and walking modes. The worst predicted period is the EV period, with an absolute error of 18.2% for transit and 5.95% for the car passenger mode. Regarding car use, although the model accounts for car ownership changes, the considerable economic growth of Temuco during the study period and the consequent growth of the city's vehicle fleet may be an effect that is challenging to capture fully. This effect can be observed in Figure 29, which shows the mode splits for the whole day for each year. As shown by the figure, there appears to have been a shift between the two years towards auto (C and P) modes and "other" modes at the walk and transit modes' expense. This result may explain part of the over-prediction of transit usage and the under-prediction of auto usage in the 2013 case, combined with the mode choice model's tendency to slightly over-estimate transit usage in the base case.

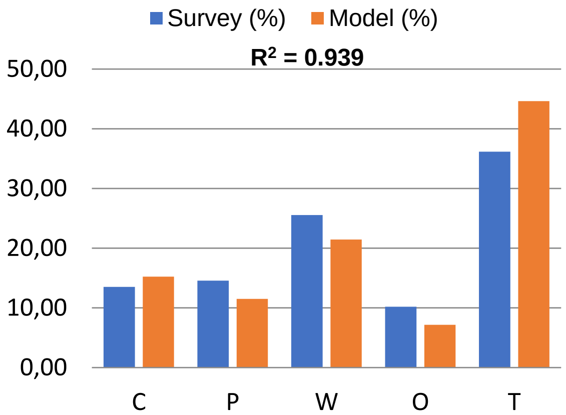

Figure 25. Predicted mode split AM period.

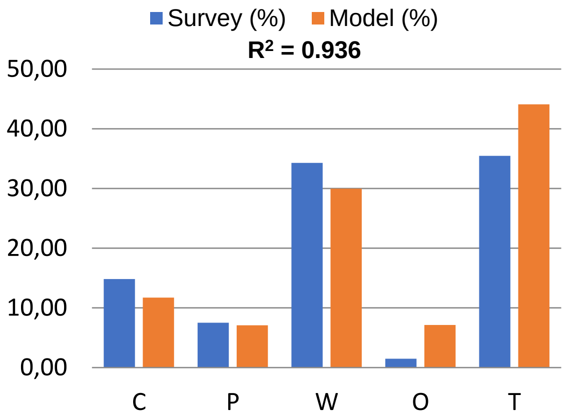

Figure 26. Predicted mode split MD period.

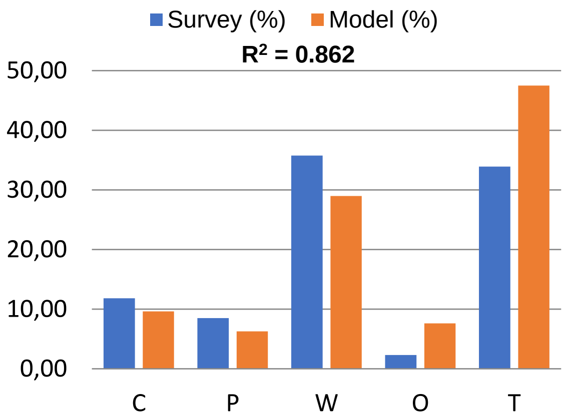

Figure 27. Predicted mode split PM period.

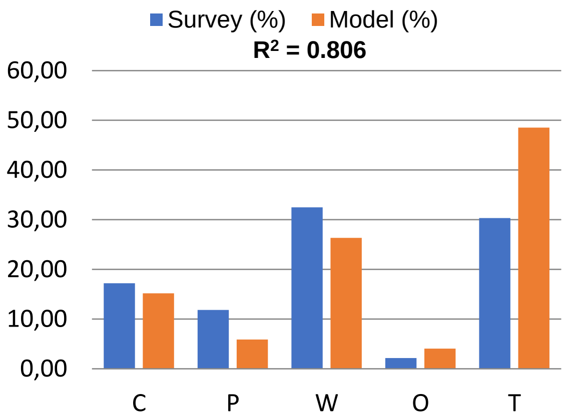

Figure 28. Predicted mode split EV period.

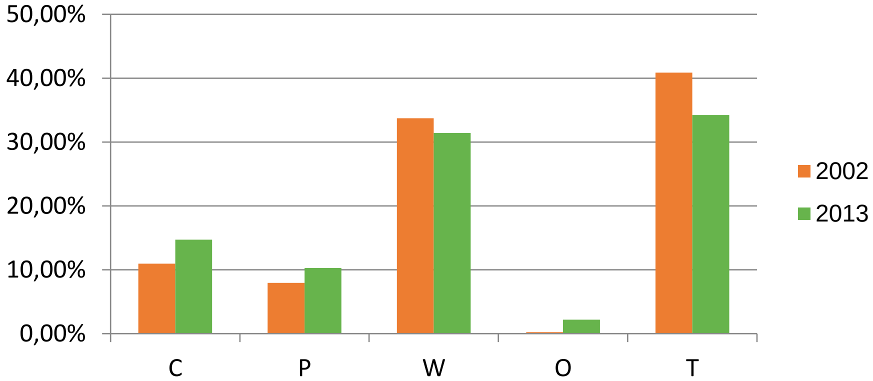

Figure 29. Mode splits comparison.

4.2.4. Trips

Finally, vehicle counts and predicted trip distributions were analyzed. The vehicle count data extracted from the 2013 survey consisted of manually generated counts, and, similarly to the 2002 analysis, vehicle turns were excluded from the comparison. The criteria for defining vehicle count locations were to make cuts in the city to account for the flows that cross the city towards downtown or vice versa. The Adjusted R^2 value obtained for vehicular flow validation was 0.62, which is not overly precise. Still, the result is expected since both the prediction of activity distribution and the mode splits have a low fit.

Figures 30 and 31 show the predicted trip destination and origin for the AM period, respectively. The model underestimated around 3% for the totality of produced and attracted trips in the AM period. Although the prediction performed better than the previous case, it still has some important differences, such as the predicted trip origins in zones 1 and 3, and the attracted trips in zone 6. Table 4 shows the relative error of the predicted trip distribution between the city's areas for the entire sample in the AM period to complement that information. While the predicted trip distribution is more precise than the base year's trip distribution, some discrepancies exist in particular OD pairs. For instance, there is an important overestimation on OD pairs, such as 1–5 and 1-6.

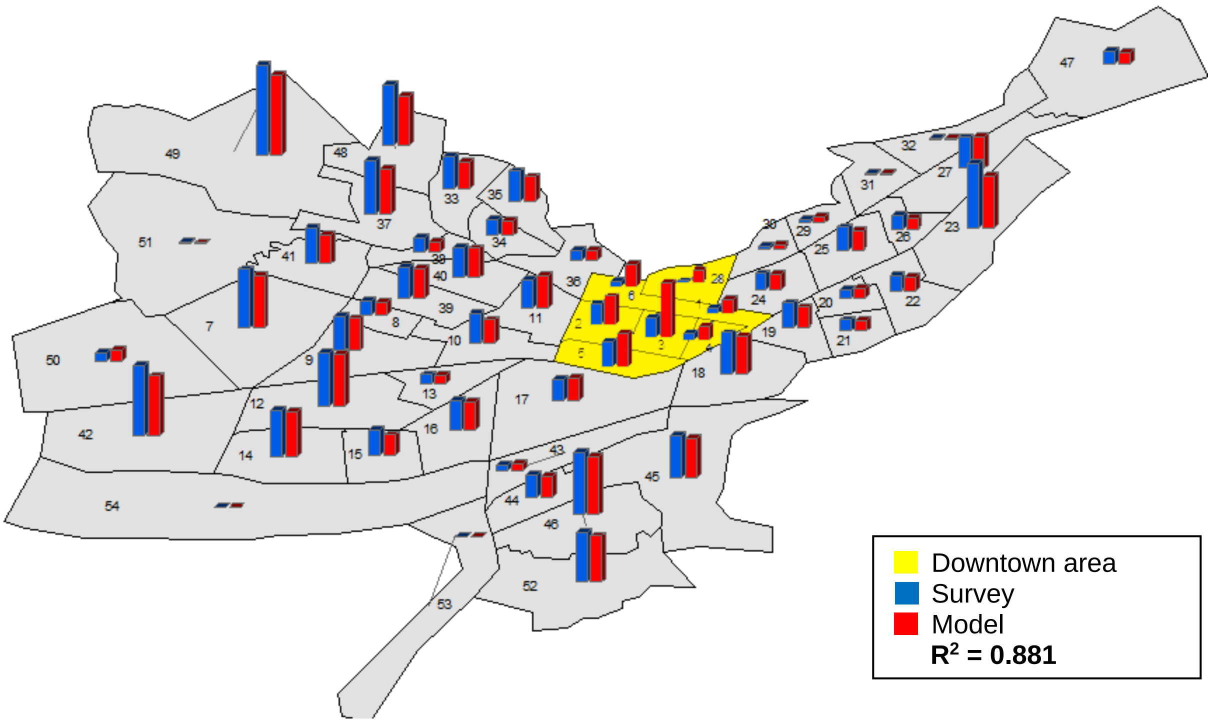

Figure 30. Predicted trip origin AM period.

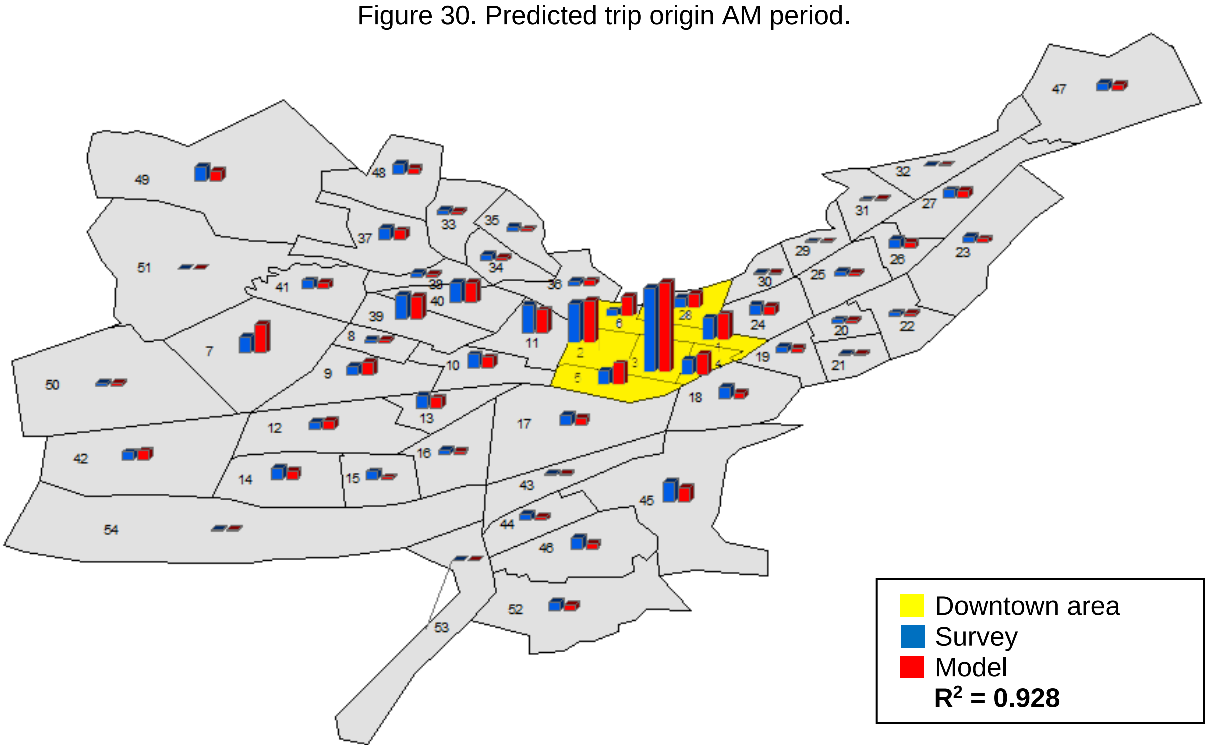

Figure 31. Predicted trip destination AM period.

O/D	1	2	3	4	5	6	TOTAL
1	87.7%	107.8%	77.6%	45.6%	626.2%	218.6%	103.9%
2	-15.4%	-51.9%	-3.2%	-84.2%	64.5%	18.0%	-37.3%
3	23.5%	-17.1%	-54.6%	16.5%	8.6%	12.6%	-10.0%
4	9.6%	16.1%	-27.9%	-55.5%	-76.3%	-55.5%	-27.1%
5	19.3%	-67.6%	10.0%	-23.4%	-60.7%	-53.1%	-32.7%
6	43.0%	-11.0%	-57.1%	-42.8%	-34.0%	-55.6%	-19.8%
TOTAL	20.5%	-32.3%	-35.1%	-43.2%	-39.2%	-29.3%	-21.1%

Table 4. Predicted relative error of trip distribution on the AM period.

5. Conclusions and expected future results

Although activity-based models have significant advantages to study transport-related policies, there are very few applications in the Global South and still little experience with their capabilities to replicate and predict travel-related behavior. This paper reports the replicability and temporal transferability of the activity-based model TASHA in the Chilean city of Temuco to investigate this issue. The study highlights the possibilities and challenges involved in this context.

Regarding the model's replication, the estimation of activities is consistent with what was observed in the travel survey. The estimated mode split represents the survey data for each period of the day. Finally, regarding the travel estimates of the Temuco, although TASHA has some issues with replicating trip distribution on some OD pairs, it performs reasonably well for the overall trip origin and destinations and traffic flows. Also, note that trip distribution is a challenging component of comprehensive travel demand model systems, regardless of the modeling approach. Despite TASHA's flexibility in using conventional data, the exercise also highlighted the need for other specific aspects such as identifying each worker's work zone and additional information to estimate location choice and auto and transit assignment. These results suggest that TASHA works well in an urban context different from the GTHA and confirms that using an activity-based model in a Chilean context is feasible and provides a reasonable replication of a context different from the model's current application.

The activity attribute prediction was very acceptable regarding temporal transferability, with end-time distribution presenting the lowest fits. Similarly, mode split prediction was reasonably good, although it showed some issues in predicting car usage. In the case of trip prediction, trip origin, destination, and distribution, the model performed even better than the base case. Finally, the vehicle count, the result was not particularly precise, although this is expected since both the end-time distribution and mode splits have a somewhat low fit.

Those prediction issues highlight the current limitations travel and activity-based models have, especially when considering the long span between the calibrated and predicted year. As discussed before, between 2002 and 2013, policies were implemented to change the weekly work hours and the school hour's structure, affecting work and study end times. Although TASHA incorporates car ownership changes, part of the mode split issues may be due to the rapid economic growth and consequent car purchase. In that regard, the results presented here indicate, on the one hand, the need for coupling activity-travel models with land-use modeling frameworks that could consider longer-term urban policies. However, on the other hand, these issues – particularly the end times fit - also highlight the importance of considering broader policies than the usual transport and urban-related ones. Still, others may affect crucial time-scheduling behavior, such as working and studying hours.

Another important lesson from this exercise is data, often overlooked when studying the validation and prediction of activity-based models. On the one hand, TASHA is sufficiently flexible to adapt to conventional data such as those available for Temuco, facilitated by this OD survey's good quality.

However, OD surveys in Chile occur only every ten years due to cost limitations and use a relatively low sample size compared with several similar datasets from the Global North. In addition, transport agencies in the Global South apply these models using a business-as-usual scenario as they do not have reliable land use forecasts. These aspects may influence the model's capability to replicate and predict behavior. TASHA performs reasonably well despite these limitations, especially at the aggregated levels, which are the most critical policy analysis. Future trends on new data sources may improve these issues on temporal lags and sample size.

Even though traditional models are still the state of the practice in countries such as Chile, this exercise provides valuable proof of principle of several arguments about the advantages of activity-based models such as TASHA. First, the study showed the model's capabilities to capture current and future behavior despite data and different context limitations. Second, the model characteristics allow the analysis to concentrate on predicted trips, as traditionally, as well as on activity characteristics, making more transparent assessing their qualities. Finally, and more importantly, the focus on activities, such as end times, emphasizes the critical need to incorporate more explicitly policies beyond those traditionally considered in these contexts. Future work should further explore these potential strengths.

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