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Original Article

Integrated Trip Distribution Modelling using Household Survey Data, Doubly Constrained Gravity Model, and R-Based Calibration: A Case Study of Bi-nuclei Cities

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Abstract *- Recent research has shown that it is vital to comprehend the distribution of trips within urban areas to undertake successful transport planning, especially within the municipal areas that grow at a dominant rate. This paper is a model of the trip distribution of Sangli-Miraj-Kupwad Municipal Corporation based on a household survey and two complementary analytical models. On the one hand, the structured Household Interview Survey provided socio-economic and travel-related data, which, in turn, created an in-depth portrait of household features, travel purposes, and mode preferences in 12 Traffic Analysis Zones. Based on these data, an Origin-Destination matrix was built using the Doubly Constrained Gravity Model with the help of Excel so that both trip productions and attractions were equal to the observed values by balancing* α_i *and* β_j *factors with each other. Second, the deterrence parameters were estimated in RStudio, and inter-zonal flows were sensitive to the cost of traveling, providing another independent statistical assessment of how the model behaves. A combination of these two methods allows obtaining more concise insight into the interactions in spatial travel using strict matrix balancing and the estimation of behavioural parameters. The framework that has been obtained offers an efficient representation of mobility patterns and helps make decisions based on data related to the planning of urban transportation in the study area.*

Keywords *- Gravity model, Household Size, Trip distribution, Trip Matrix.*

1. Introduction

Trip distribution is the basic element of the travel demand modelling that aims to predict and analyse the spatial interaction of a trip between the zones of origin and destination within and between regions [1-4]. It is important because it helps to model the spread of travel demand across the transport network, predict the infrastructure investment, forecast the flow of traffic, and impact the development of the regions [5-8]. Within the structure of modern computational modelling, R software provides an open-source, reproducible, and flexible system to implement these models in terms of packages such as spatialreg, sf, tidyverse, and caret--allowing the integration of econometric, spatial, and machine learning frameworks for enhanced predictive accuracy [9-12].

The theory of trip distribution is based on the idea of the gravity theory, which compares the movement of people between two regions to the gravitational force that has a gravitational attraction proportional to their population and inversely related to distance [1, 2, 13, 14]. Classical gravity models have become hybrid in nature, and the destination attractiveness and impedance factors are rated under econometric and statistical inference [15, 16]. It allows the evolution of it by giving statistical strength and modelling transparency by the use of regression-based calibration, Poisson pseudo-maximum likelihood estimation, and Bayesian hierarchical models [6, 7, 17, 18].

Contemporary trip distribution studies go beyond the conventional models by considering spatial dependence and temporal heterogeneity, which is well-suited to the analysis with the help of spatial econometrics and panel data models [19-22]. These are the Spatial Autoregressive (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM), which can be estimated using the packages spatialreg and spdep to estimate interzonal interactions, neighbourhood effects simultaneously [5, 6, 23].

These models deal with one of the fundamental issues of trip distribution, the interdependency between origins and destinations, in a better way than the simplistic assumptions of independence of classical models [8, 13, 19, 24]. The shift toward data-driven and machine learning paradigms has further expanded the methodological landscape [25].

The most common empirical studies have continuously been able to detect the major determinants affecting the distribution of trips, such as population, GDP, infrastructure, and travel cost [26-30]. These factors can be combined into R-based models and visualized dynamically as well as sensitivity analysed [11-12]. Finally, trip distribution modelling with R software is a combination of both classical transportation theory and modern data science. It is the flexibility of R to support statistical, spatial, and machine learning paradigms that enables researchers to no longer work with their simplistic assumptions but instead adopt adaptive, hybrid models, which reflect real-life mobility. It is open-source, reproducible, hybridized R-based frameworks that balance behavioural fidelity with computational sophistication, that are the future of trip distribution analysis, between academic rigour and policy relevance.

However, although recent developments show an increasing role of spatial econometrics and machine-learning-enhanced modelling, the practical implementation of trip distribution in most Indian medium-sized cities still uses detailed household-level data and classical formulations of gravity. In these situations, large-scale passive mobility datasets are lacking, and structured Household Interview Surveys (HIS) represent the surest of available methods of capturing zone-to-zone travel behaviour.

This paper, therefore, uses an extensive HIS to be conducted in 12 Traffic Analysis Zones (TAZs) in the Sangli-Miraj-Kupwad Municipal Corporation to produce observed trip-productions, attractions, and socio-economic features. A balanced Origin-Destination matrix is then built by the Doubly Constrained Gravity Model, and the calibration of deterrence parameters and sensitivity to costs is evaluated using RStudio. In this way, the theoretical bases addressed above are supported by empirically gathered local information and provide analytical transparency and reproducibility.

Although there have been great improvements in trip distribution modelling, the current studies are more or less following two parallel lines. Recent research is moving towards the application of spatial econometrics, machine learning, and big-data-based approaches based on passive sources of mobility, including mobile phone or social media data; nevertheless, the approaches are less applicable to medium-sized Indian cities, as the unavailability of data, access issues, and institutional restrictions are present.

However, classical gravity-based models using household survey data are still popular, yet most of these applications mainly aim at balancing origin-destination matrices without explicitly investigating how sensitive household trips are to the cost of travel. This leaves a research gap between structurally balanced trip distribution and behaviourally understandable demand estimation of constrained data in urban situations. The originality of the current paper is that it suggests an integrated model that will provide structural consistency and behavioural realism simultaneously through the combination of a Doubly Constrained Gravity Model and independent R-based estimation of deterrence parameters with the primary household survey data.

In contrast to current literature that takes one of the two options of either employing a sophisticated data-driven methodology without rigorous production-attraction testing or using a conventional gravity model without behavioural calibration, this study simultaneously assesses the two dimensions in the context of a single transparent and reproducible workflow. The case of the bi-nuclei urban system of the Sangli-Miraj-Kupwad Municipal Corporation can be seen as evidence of the practical applicability and methodological value of the proposed approach to transportation planning of medium-sized cities in developing countries.

2. Literature Review

The practice of trip distribution modelling has been a part of travel demand analysis since the beginning of time, and the theoretical basis of most of the practice is based on gravity models [31-34]. Initial observations formed the comparison of spatial interaction with gravitational attraction by proving that trip flows between zones are proportional to trip productions and attractions and inversely correlated to travel impedance. They were extensively used because of their simplicity, interpretability, and appropriateness to the analysis at the planning level, especially when behavioural information on a fine level was unavailable [35-37].

Gravity models were formulated singly and doubly constrained to make sure that either trip productions were correct or both productions and attractions would be correct [38, 39]. Some studies proposed constrained gravity models that aimed to enhance realism by requiring that the zonal trip totals should be observed [40]. The models have been widely used in urban and intercity settings, particularly when a household travel survey is the source of data input [41]. This becomes a common instrument in the transportation planning practice due to its capability to produce balanced origin-destination matrices [42].

Simultaneously, the development of statistical and econometric models has resulted in behaviourally calibrated trip allocation models [43]. Deterrence functions and quantifying travel cost sensitivity have been estimated using regression-based calibration [44], Poisson and Negative binomial models [45], and entropy-maximization models [46]. More recently, spatial econometric models like spatial autoregressive and spatial error models have been proposed so as to explicitly reflect interdependence between pairs of origin-destination by overcoming the assumptions of independence of classical gravity formulations [47].

As more passive mobility data on a large scale becomes increasingly available, more recent papers have dealt with machine learning and data-driven methods of trip distribution modelling [48, 49]. These techniques utilize the data of mobile phones, GPS tracks [50], and social media to provide a more complex nonlinear movement behaviour and spatiotemporal dynamics [51-53].

The critical review of the available trip distribution techniques indicates that there has been a structural-behavioural gap in the accuracy and interpretation of the behaviour of various trip distribution methods. The classical gravity models, especially the ones that have been implemented with the help of household survey data, are useful in producing balanced origin-destination matrices but usually assume the sensitivity of travel costs implicitly by using predetermined impedance functions without behavioural calibration. Conversely, more recent data-driven, spatial econometric, and machine-learning-based models explicitly model behavioural reactions and intricate spatial interactions; however, they use large-scale passive mobility data, which are not generally accessible or feasible in medium-sized cities in developing nations.

As a result, there is a methodological discontinuity between the structurally balanced models, which have no behavioural validation, and the behaviourally rich models, which are either inconsistent in terms of production-attraction or applied to the real world. The current research paper fulfils this research gap by incorporating a Doubly Constrained Gravity Model within a regression calibration of deterrence parameters using primary data of households surveyed. This combined method guarantees the existence of a strict origin-destination balance as well as the clear estimation of the sensitivity of the travel costs in a single and transparent framework that is reproducible, closing the divide between the conventional planning-based approaches and behaviourally-oriented analytical models.

3. Methodology

We have selected the Sangli Miraj Kupwad Municipal Corporation area as a case study. Traditionally, Sangli and Miraj were two separate cities, which had their own municipal governments; however, as the cities expanded, especially with the industrialization of Kupwad, the necessity to have a unified government was felt. Sangli and Miraj are bi-nuclear cities. The geographical setting of the study is composed of 74 municipal wards that were properly consolidated into 12 Traffic Analysis Zones (TAZs) to ensure uniformity of the space in the modelling.

The study region was subdivided into twelve Traffic Analysis Zones (TAZs) of the spatial structure of Sangli-Miraj-Kupwad Municipal Corporation. The zonal lines were drawn according to the areas of administrative wards, continuity of the built-up area, population density, and functional land-use features. A unique colour is provided to each zone to be easily distinguished to ease analysis of data later in the household survey, of the OD flows and inter-zonal travel patterns. The household sampling model was developed by the Cochran Formula with Finite Population Correction (FPC) in calculating the minimum representative sample size per zone. This provided the proportional coverage of all zones without impairing the statistical reliability in the calculation of inter-zonal mobility.

3.1. Case Study

The two cities Sangli and Miraj, called a bi-nuclear city, which are very historic cities of Maharashtra, have transformed into major metropolitan cities since they were established in the Middle Ages and ancient India. The Sangli-Miraj-Kupwad Municipal Corporation (SMKMC) was established in 1998 to manage the rapidly developing urban agglomeration composed of the twin cities of Sangli and Miraj, as well as the neighbouring town of Kupwad. The SMKMC was established to take care of the requirements of comprehensive urban planning and infrastructure development in this area, which happens to be in rapid population and industrial growth. In the 2011 census, Sangli-Miraj-Kupwad region had a population of 502,793.

A comprehensive picture of the household travel characteristics within the 12 traffic zones served as the dependent variable for subsequent modelling. Independent variables, in this case, the household income and vehicles, were identified as the direct extraction of survey responses (purposes of trips, mode preference). This household survey design offered more intense behavioural interpretation relative to passive data sources, making it possible to undertake powerful mobility pattern modelling throughout the investigation region. Figure 1 shows the Zoning of the area.

A structured Household Interview Survey (HIS) was used to gather primary data for this study in the twin cities. This study utilized direct household-level data collection, unlike the studies that used social media footprints [51-53] and passively obtained mobility data [54-56]. This research employed direct household-level data acquisition, enabling the collection of high-precision socio-economic and travel-behaviour information.

Similar to other research, data collection was performed based on a structured questionnaire in the form of face-to-face interviews [57-60]. The Survey allowed each respondent to give extensive data regarding the characteristics of the homes, demographic structure, level of income, owning vehicles, and attributes of personal trips. Origin-Destination (OD) information was captured for each member of the household, namely the purpose of the trip, mode of choice, travel time, frequency, and cost. The OD matrices in the further analysis were based on these person-level trip entries.

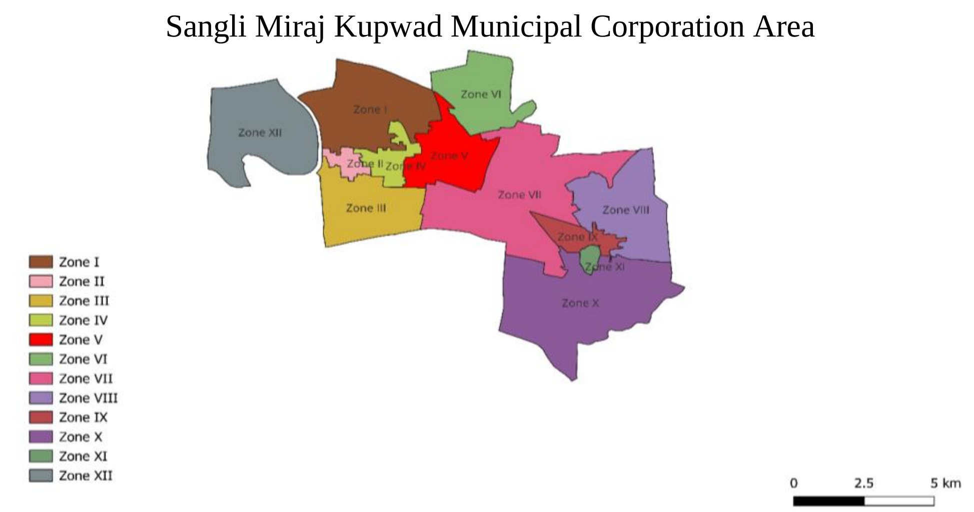

Fig. 1 Zoning map of SMK municipal corporation area

Table 1. Summary of household survey characteristics

Household Size		**Number of Children Below age 4**				**Trip Purpose**	
No of Persons	Percentage	HH Size	Children_0	Children_1	Children_2	Trip Purpose	Percentage
1	0.60%	1	0.60%	0.50%	-	Work	38.70%
2	20.90%	2	27.20%	1.60%	-	Business	12.10%
3	31.40%	3	27.10%	53.60%	8%	School	19.40%
4	35.10%	4	33.50%	30.90%	78.40%	College	11.30%
5	9.70%	5	9.20%	11.20%	11.40%	Shopping	18.50%
6	1.80%	6	1.90%	1.60%	2.30%		
7	0.50%	7	0.50%	0.50%			
Total Vehicle/ HH		Occupation			Mode of Travel		
Total Vehicle/ HH	Percentage	Occupation	Male	Female	Mode of Travel	Male	Female
0	6.30%	Govt. Service	3%	1.60%	Walk	6.90%	25.40%
1	46.80%	Private Service	48.70%	24.30%	Bus	7.40%	9.50%
2	37.70%	Own Business	14.90%	9.80%	Car	4.30%	1.10%
3	5.70%	School Student	20.20%	16.50%	Two-Wheeler	62.50%	32.30%
4	3.40%	College Student	11.90%	9.90%	Auto	10.50%	23.70%
5	0.10%	OT Other	1.30%	37.90%	Bicycle	8.40%	8.10%

The survey captured the following key variables for each household:

- Household characteristics: dwelling type, ownership status, household size, and gender composition.
- Socio-economic attributes: gross monthly income categories, occupation types, and employment status.
- Vehicle ownership: car, two-wheeler, and bicycle availability.
- Individual trip details: origin, destination, purpose (e.g., work, school, shopping), travel mode, travel frequency, travel time, and travel cost.
- Perception-based indicators: The availability of transport, satisfaction with the current services, perceived difficulties, Willingness to Sell (WTS), and Willingness To Pay (WTP) for better transportation systems.

The household travel behaviour is critical to the development of efficient transportation planning strategies and modelling urban mobility trends. A household survey can be useful in giving detailed information on socio-economic factors, purpose of trip, mode of transport, and ownership of vehicles, and therefore, it is possible to estimate the travel demand correctly.

The data gathered assists in determining the effect of the demographics on travel decision-making and general trends in mobility. This kind of comprehensive information is the basis on which Origin-Destination matrices can be built, and analytical models such as the gravity model can be used. The proposed research employs the data of household surveys to study the nature of traveling and to assist in making evidence-based transport planning.

Screening of the data eliminated incomplete records and inconsistent entries. OD entries that had no origin or destination, or purpose of trip, were eliminated. The eliminated data were further grouped into zone-to-zone OD flow tables through the association of each surveyed household with its respective TAZ. Internal trips (starting and ending within the same household parcel) remained because they give the local mobility trends. The characteristics are indicated in Table 1.

3.2. Trip Distribution Modeling

3.2.1. Gravity Model

One such popular technique that is used in transportation planning to estimate spatial interactions between origin and destination areas is the gravity model. It presumes that the generating and enticing ability of the zones is directly proportional to the respective trip interchange to the inverse spatial fraction between the areas.

Basic (Unconstrained) Gravity Model

The simple gravity model gives a preliminary estimate of the number of trips between zones without making any kind of matching of aggregate productions or attractions. It expresses trip flows as in Equation 1:

$$T\_ij = k * (Pi * Aj) / f(cij) \tag{1}$$

where (Pi) and (Aj) denote the trip production and attraction of zones (i) and (j), respectively; (cij) represents travel cost or distance; f(cij) is a deterrence function; and (k) is a scaling constant. Although simple, this form does not guarantee that the resulting OD matrix matches observed totals.

Doubly Constrained Gravity Model

To generate more realistic trip distributions, the doubly constrained gravity model will create both the origin and destination eliminations, so that the aggregate of these distributed trips will be equal to the observed totals in each zone. The model is expressed as in Equation 2:

$$T\_ij = \alpha\_i * O\_i * \beta\_j * A\_j * f(c\_ij) \tag{2}$$

where (O_i) and (A_j) are the known trip productions and attractions, and (α_i) and (β_j) are balancing factors computed iteratively to satisfy, as given in Equation 3:

$$\Sigma\_j\ T\_ij = O\_i \quad \text{and}\ \Sigma\_i\ T\_ij = A\_j \tag{3}$$

This formulation yields a fully balanced OD matrix that accurately reflects observed system totals.

The Doubly Constrained Gravity Model is used in this study, and the reason is that this model offers a statistically consistent and realistic means of distributing trips collected as a result of the household survey. It supports both destination attractions and origin productions simultaneously, in contrast to simple or unimpeded models, so that the OD matrix will represent observed travel patterns. The model is calibrated and internally consistent by determining the trip flows based on the balancing factors (ai and bj) that allow the total totals to be maintained, and the model is terminated.

4. Results

This study analyses household travel behaviour using two complementary types of results to ensure a comprehensive understanding of mobility patterns. The initial product is the Trip Matrix, which was created using the gravity model and reflects the allocation of travel between two or more zones, and is the heart of the travel demand estimation. The second output is created with the use of RStudio, in which statistical analysis and visualization procedures are used to analyse the socio-economic characteristics, mode choice patterns, and household features. The Trip Matrix is analysed together with the R-based analytical outputs to provide a complementary scale of spatial and statistical insights to define trip distribution. The combination of this method increases the reliability and accuracy of the trip distribution results.

4.1. Trip Matrix

This research paper has calibrated the trip distribution process with the Doubly Constrained Gravity Model, whereby both the origin productions and destination attractions should be fulfilled at the same time. The balancing factors α_i and β_j were calculated in an iterative manner to balance the totals of the rows and columns till a convergence was reached. The α_i values (under the CF Row column) are used to correct the productions of each zone of traffic, such that the total of the outgoing trips corresponds to the household survey totals. Equally, the β_j values (represented as CF of attractions) modify the column sums to make distributed trips consistent with anticipated zone-based attractions. All these correction factors combined obtain a complete balance of the final Origin-Destination matrix that is internally consistent and reflects the real-life travel behaviour in the study region. Table 2 indicates the trip matrix analysis results.

Computed Values

Average Origin Balancing Factor (α_i) =0.9969

Average Destination Balancing Factor (β_j) =1.031

Sum of Squared Errors (SSE) =3.370

Table 2. Trip matrix

Traffic Zone	**Trips**												**Production (Pi) Expected**	**Production**	**CF Row**
	1	2	3	4	5	6	7	8	9	10	11	12			
1	235	133	83	99	115	95	51	46	60	39	31	114	1100	1099	1.013
2	79	62	68	53	42	27	20	18	25	17	13	54	479	479	1.016
3	64	88	91	52	58	34	32	27	39	27	20	51	584	584	1.017
4	83	76	57	40	70	35	25	20	28	18	14	36	502	502	1.027
5	52	32	34	38	73	52	41	26	36	21	17	25	448	448	1.013
6	50	24	23	21	60	80	32	28	34	19	16	24	410	410	0.989
7	58	39	47	34	102	68	127	94	158	68	65	37	897	897	0.999
8	23	15	18	12	29	27	42	112	130	50	62	17	536	536	0.984
9	24	17	21	13	32	26	57	106	128	74	141	18	658	657	0.993
10	17	12	15	9	20	16	25	43	77	82	64	13	394	394	0.974
11	13	9	11	7	16	13	24	52	146	64	41	10	407	407	0.990
12	44	35	26	17	21	18	13	13	17	12	9	86	309	309	0.948
Attraction (Aj)	773	620	483	489	697	423	495	504	959	385	546	347	6724	6724	
Expected Attraction (Aj)	737	539	490	392	637	490	490	588	881	495	497	488			
CF	0.95	0.87	1.02	0.80	0.91	1.16	0.99	1.17	0.92	1.28	0.91	1.40			
Corrected Attraction	740	542	493	395	640	491	489	585	876	492	493	486	6723		
Diff. check	0.491	0.608	0.5550	0.643	0.359	0.094	-0.1383	-0.5961	-0.6182	-0.6939	-0.7397	-0.3373			

4.2. Modelling Trip Distribution with RStudio

RStudio trip distribution models are a powerful and versatile analytical space that can be used to study the spatial distribution of travel. R can be used to combine statistical modelling, matrix operations, and visualization, which makes it an appropriate tool to calibrate gravity models and analyse trip flows between zones. R guarantees transparency, reproducibility, and accuracy in the control of parameters like alpha, beta, and deterrence functions through programmable workflows. The analysis of the household survey data in RStudio not only allows for a proper estimation of the distribution of trips but also provides more insight into the observation of the zone-to-zone travel behaviour. Figure 2 gives details about the input file, while Figure 3 explains the output file.

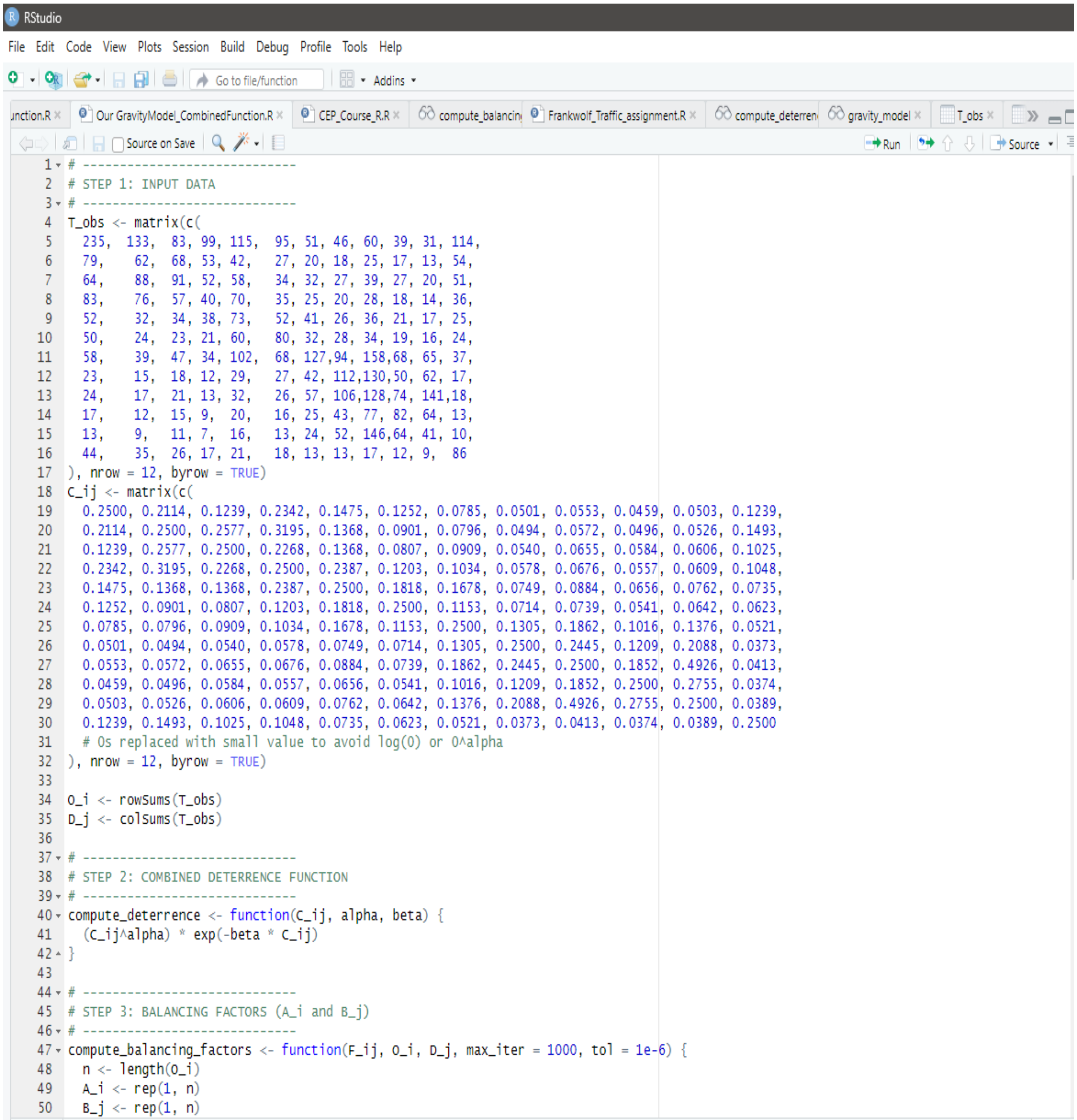

Fig. 2 RStudio input

```
+   control = list(maxit = 1000)
+ )
>
> # ----------------------------
> # STEP 7: FINAL OUTPUT
> # ----------------------------
> optimal_alpha <- result$par[1]
> optimal_beta  <- result$par[2]
> T_model_final <- gravity_model(O_i, D_j, C_ij, optimal_alpha, optimal_beta)
>
> cat("ptimal α:", round(optimal_alpha, 4), "\n")
ptimal α: 0.9995
> cat("ptimal β:", round(optimal_beta, 4), "\n")
ptimal β: 0.001
> cat("Minimum SSE:", round(result$value, 4), "\n")
Minimum SSE: 10.875
> cat("\nModelled Trip Matrix (Doubly Constrained):\n")

Modelled Trip Matrix (Doubly Constrained):
> print(round(T_model_final, 2))
        [,1]   [,2]  [,3]  [,4]   [,5]  [,6]   [,7]   [,8]   [,9] [,10]  [,11]  [,12]
 [1,] 235.63 132.76 82.92 98.77 114.91 95.33  51.05  46.16  60.27 39.14  30.56 113.50
 [2,]  78.78  62.06 68.14 53.25  42.13 27.13  20.46  17.99  24.64 16.72  12.63  54.06
 [3,]  63.64  88.14 91.08 52.10  58.05 33.48  32.19  27.10  38.88 27.12  20.05  51.15
 [4,]  83.28  75.67 57.24 39.78  70.13 34.56  25.36  20.09  27.79 17.92  13.96  36.22
 [5,]  52.05  32.17 34.26 37.68  72.87 51.80  40.82  25.83  36.05 20.93  17.33  25.21
 [6,]  49.78  23.87 22.78 21.40  59.71 80.22  31.60  27.73  33.95 19.45  16.44  24.07
 [7,]  57.74  39.01 47.44 34.02 101.93 68.46 126.67  93.71 158.11 67.53  65.15  37.24
 [8,]  23.14  15.20 17.70 11.95  28.58 26.63  41.54 112.67 130.33 50.45  62.06  16.74
 [9,]  24.51  16.89 20.60 13.41  32.37 26.44  56.85 105.73 127.88 74.13 140.39  17.79
[10,]  16.64  11.98 15.02  9.03  19.64 15.83  25.38  42.77  77.48 81.81  64.24  13.17
[11,]  12.89   8.98 11.02  6.98  16.13 13.28  24.29  52.21 145.58 63.73  41.21   9.69
[12,]  43.99  35.32 25.83 16.65  21.57 17.87  12.76  12.94  16.95 12.01   8.90  86.20
>
```

Fig. 3 RStudio output

Computed Values

αi=0.9995, βj=0.001, SSE=10.875

5. Discussion

Both the Excel-based Doubly Constrained Gravity Model and the RStudio calibration provide an in-depth insight into the patterns of trip distributions in the study area. The trip matrix found with the use of the gravity model shows good internal consistency with the mean balancing factors (a = 0.9969 and b = 1.031). The two values are close to 1.0, meaning that few modifications had to be carried out to match the modelled productions and attractions to the observed household survey totals. The fact that the SSE of 3.3705 is low additionally verifies that the gravity model was very convergent, and an OD matrix was obtained, which approximates real trip-making behaviour and at the same time extracts the strict row and column balancing.

Conversely, the RStudio calibration concerns the estimation of the behavioural parameters of the deterrence function, not the strict structural balancing enforcement. The approximate values (a = 0.9995 and b = 0.001) indicate that the cost sensitivity is very linear and the exponential rate of decay is very low, which is in accordance with the fact that the urban structure of the area is rather compact, and the inter-zone distances are rather small. It is expected that the SSE of the R (10.875) is greater than the Excel model, which is not due to the ineffectiveness of the R model but rather because the two models assess different levels of accuracy. The Excel gravity model compels productions and attractions to be identical by the balancing process of iteration, which causes a reduction in SSE, of course. In the meantime, the R model considers the effectiveness of the deterrence mechanism in predicting flows between all pairs of zones without requiring row-column matching, and is therefore more susceptible to behavioural diversities. Thus, an increased SSE in R indicates wider calibration with the whole dataset, as opposed to model inaccurateness.

In general, these two modelling methods are complementary; the gravity model based on Excel guarantees structural validity, whereas the model in RStudio confirms the behavioural shape and sensitivity of the process of tripping distribution. Collectively, they offer a strong and trustworthy collection of travel trends to build an analytical base on transportation planning and decision-making in the subject area.

6. Conclusion

This paper gives a comprehensive understanding of the behaviour of travel in the Sangli-Miraj-Kupwad Municipal Corporation, through the combination of the household survey and two complementary models, namely the Doubly

Constrained Gravity Model and Calibration using RStudio. The gravity model generated a balanced trip matrix with limited modification as indicated by the α_i and β_j close to 1, and a very small SSE, indicating the credibility of the survey data and a good structural fit of the model. Simultaneously, the RStudio model added to the understanding of the sensitivity of the behaviour to the making of trips and demonstrated almost linear cost effects and distance decay. Even though R generated a slightly larger SSE, this is not surprising because of its reliance on behavioural calibration and not on the strict implementation of trip totals. A combination of these methods makes the analysis more profound--Excel guarantees the correct recreation of the observed productions and attractions, and R legitimizes the deterrent effect and the behavioural authenticity of the model. The overall results not only reinforce the validity of the trip distribution findings but also prove the usefulness of a mixed-method analytical approach in transportation planning. In conclusion, this unified structure offers a strong base to predict the future demand of traveling, assess the options of the policies, and aid in making sound decisions regarding sustainable urban transportation in the area.

Author Contributions

A.S.M. conceived, designed, and performed a review of the literature; analysed the data; wrote the paper; and A.V.S. and V.V.K. reviewed and proofread the manuscript. All authors have read and agreed to the published version of the manuscript.

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