Australasian Transport Research Forum 2023 Proceedings
29-01 December, The University of Western Australia
Publication website: http://www.atrf.info

Reducing run times in CUBE using integer demand in assignment

Alan Kleidon[1], Gayath Chalabi[2], Erna Sukardi[3], James Parrott[4] ,Steven Piotrowski[5]
[1] SMEC Australia Pty Ltd , Perth, Australia
[2] SMEC Australia Pty Ltd, Melbourne, Australia
[3] SMEC Australia Pty Ltd Melbourne, Australia
[4] SMEC Australia Pty Ltd Adelaide, Australia
[5] SMEC Australia Pty Ltd , Perth, Australia
Email for correspondence: Alan.Kleidon@smec.com

Abstract

As strategic transport models become more complex, excessive run time can become challenging. The minimum time needed for complete model runs can extend to several hours per scenario and for some strategic transport models, even days.

Highway assignment steps are substantial contributors to strategic model run time. The loop structure of many strategic transport models requires assignment processes to run multiple times.

This investigation is limited to Bentley System's multimodal transportation and land-use modeling software Cube Voyager. Run time savings were achieved for the CUBE Highway when real number demand matrices are replaced with integer only matrices.

Two integerisation methods were tested, bucket rounding and a pseudo-random method based on the inverse of a Poisson distribution. The integerisation method did not affect the time saving. The different methods produced different variations in model results.

1. Introduction

The time taken for a strategic transport model to complete a single scenario is a critical issue, especially with respect to project timeframes. Excessive run time erodes the usefulness of the model and can hinder the team's ability to develop and test options efficiently. The impact of long run times is particularly acute if a scenario cannot be run overnight. Testing and development cycles can be significantly slowed.

One of the contributors to long run times in strategic transport models is the Highway Assignment step. This step involves assigning traffic flows to specific routes on the transport network, taking into account factors such as congestion, travel times, and other network characteristics. As the size and complexity of transport networks increase, so does the computation requirement, leading to longer run time for Highway Assignment. The iterative process of strategic transport models means that time increases or reductions in assignment steps are multiplied in each model run.

The problem of excessive run times is compounded by the increasing expectations of clients. As cities become more complex, there is a growing need for transport models that can provide a more detailed and nuanced understanding of the transport network.

When strategic model areas are expanded or land use zones become more granular the number of zones in a strategic model increases. Origin to destination calculations increase in proportion to the square of the number of zones. This increased computational load will cause substantially longer run time.

Fast run times for the model may be an important client objective. To achieve this goal in recent projects, the authors pursued the three approaches listed below. The first two of the listed approaches are simple good practice. This paper focuses on the third approach.

- Auditing the model process to eliminate redundant calculation;
- Maximizing the use of parallel processing; and
- Selectively replacing demand matrix values with integer-only values.

In aggregate strategic transport models that remain in use in Australia, fractions of person trips in demand matrices are normal. Use of whole number (integer) demand may be useful in strategic model assignments. In examples tested for this paper, integer demand provided faster assignments than real number demand. Potential benefits and drawbacks of this approach are discussed.

This paper provides a description of how integer demand performed in a highway assignment experiment. Two questions were addressed.

- Is a useful time reduction achieved?
- Were the results consistent enough to be useful?

This investigation used Bentley System's multimodal transportation and land-use modeling software Cube Voyager. Application of techniques described in this paper have only been considered using Cube Voyager.

This section will provide some knowledge of the main elements and methods that have been investigated in this paper.

1.1 Trip assignment

The traditional travel demand model is a series of models commonly described as a 4-step process: trip generation, trip distribution, mode choice, and trip assignment (Oregon Department of Transportation, 2018, Ortúzar et al., 2011, Saw et al., 2015).

The trip assignment stage is where specific travel modes are assigned to specific routes, taking into account the network characteristics and congestion levels (Sheffi, 1985). It is a crucial step in the travel demand model process.

The Cube "HIGHWAY" program typically builds paths for all origin-destination (OD) pairs that have a value greater than zero in the trip matrix. However, if the trip matrix has many cells with values less than one, the process can become computationally expensive. To address this issue, an integerisation method can be used to adjust the cell values for each zone, effectively reducing the number of paths being built by zeroing out trips for OD pairs with small original values.

In Cube Voyager software, the HIGHWAY assignment is an iterative process that runs towards a target convergence value(e.g., RGAP[1]).

The run time for the highway assignment step depends on various factors, including:
- The size of the highway network in terms of the number of links and nodes;
- The number of zones which determines the number of OD pairs;
- The number of user classes;
- The sparsity of the trip matrices;
- Special processing, such as select link/zone analysis, sub-area matrix extraction, intersection modelling and path file outputs; and
- Model convergence criteria.

1.2 Number of cores

The focus of this study relates to the impact of integer demand. Parallel processing options will be deemed a background issue. The most reasonable assumption is that users will already have computers running at maximum capacity. Cube users will also be aware that some options in the Highway module make parallel processing unavailable. These options include sub-area matrix creation and path files.

2. Methodology

a. Integer demand creation methods

The CUBE ROWFIX function is available for bucket rounded matrices. ROWFIX converts each cell to an integer value after adding the accumulated fractional portions from the previously treated cells. With a user definable rounding factor of 0, each cell is truncated, and the fractional remainder is carried to the next cell. With a rounding factor of 0.5, each cell is rounded to the nearest integer, and the difference between the original value and the rounded value is carried to the next cell. Bias to any column is limited by the default condition of each row calculation starting at the cell after the intrazonal cell. The intrazonal cell is the last cell processed.

The "random integer" demand was produced by:
- Selecting a pseudo random probability (p);
- Creating a Poisson distribution with a mean equal to the value in the real number demand matrix cell. X~Poi(demand); and
- Selecting an integer (I) from the Poisson distribution such that the probability of being less than or equal to this integer matches the chosen pseudo random probability. $P(X<I) < p$ and $P(X<=I) > p$

b. Highway assignment test methods

[1] The relative gap (RGAP) is a mathematical function that was introduced by Janson in 1991 In other words, RGAP is an estimate of how much longer it takes to travel on the current network compared to a network where all vehicles travel on the shortest path

To investigate the impact of integer demand on the run time and model results an experiment was run. Highway assignments were run with the original demand matrix and two demand matrices that were integerised by different methods. This experiment was conducted in a single CUBE application on a single computer with three assignment scripts:

- The three assignment scripts were identical except for input and output file names. Each script assigned 19 user classes across 5 cost functions and produced 20 skim matrices.
- The demand came from the same source and was processed as appropriate within this application.
- Each assignment was limited to 40 iterations. Post checking confirmed that all 40 of the iterations were completed in all of the 3 highway assignments.
- The same highway assignments were run and reported using different numbers of computer cores.

The following analysis was done to explore the impact of the options mentioned above:

- Demand matrix comparison at origin and destination level.
- Skim matrix comparison for car travel time.
- Highway link volume comparisons.

3. Results and analysis

a. Run time results

Table 1 shows the results of running a highway assignment example with different numbers of cores using two different assignment approaches:

- Real number assignment; and
- Integer assignment.

Times taken for the same highway assignment are tabulated below. These results indicate that:

- Application of more cores reduced the run time in line with expectation.
- Integer demand reduced the assignment run time when other influences were constant.
- The two integerisation methods did not produce appreciable time differences and are not reported separately.

The actual run time will vary depending on the size of the highway network, the number of zones, the complexity of the link and node calculations, and other factors.

Table 1: Comparison between integer real number and real number highway assignment

Highway Assignment Approach	1 core	2 cores	6 cores
Real Number Assignment	**44.1 min**	**19.4 min**	**11.3 min**
Integer Number Assignment	**25.4 min**	**11.4 min**	**7.1 min**

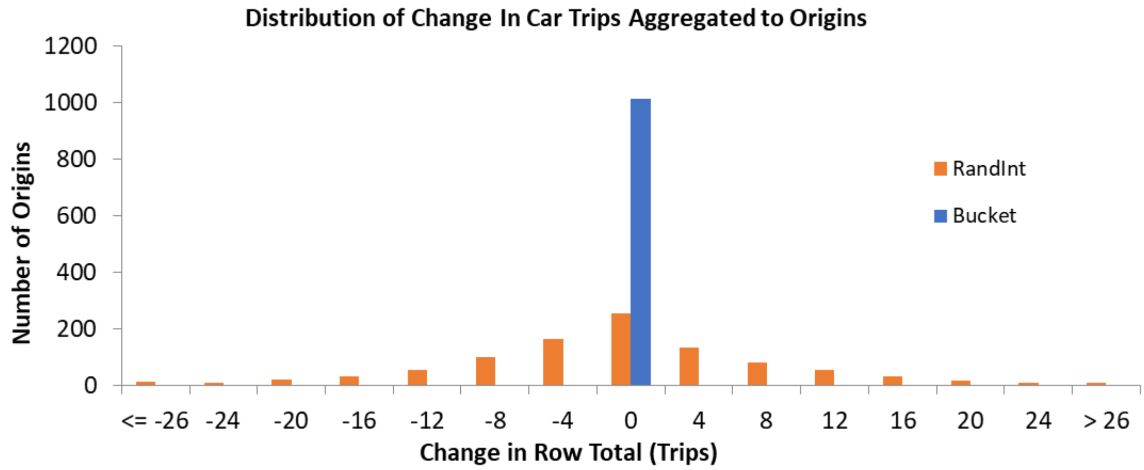
b. Assignment output results

Figure 1 and Figure 2 offer distributions of changes in matrix row and column totals when each of the integerisation methods were applied. Analysing these histograms for both the origin and destination data reveals distinct patterns in the distributions generated by the Bucket and Random Integer methods.

The data representing origins sees all bucket rounded origin values fall into the approximately zero interval. This was expected as the bucket rounding process is constructed in a manner that retains row totals to the nearest integer. The Random Integer method shows a more distributed residual. Residuals have a central tendency at zero and appear a symmetrical.

The destination data shows a less central concentration for both methods in the approximately zero interval with frequencies of 330 and 264 for Bucket and Random Integer methods respectively. Beyond this central interval, both methods display a gradual decrease in frequency with distance from zero. Despite this similarity, the Bucket method has generally higher frequencies in intervals closer to the central point compared to the Random Integer method.

Figure 1: Car journey to work matrix origin totals

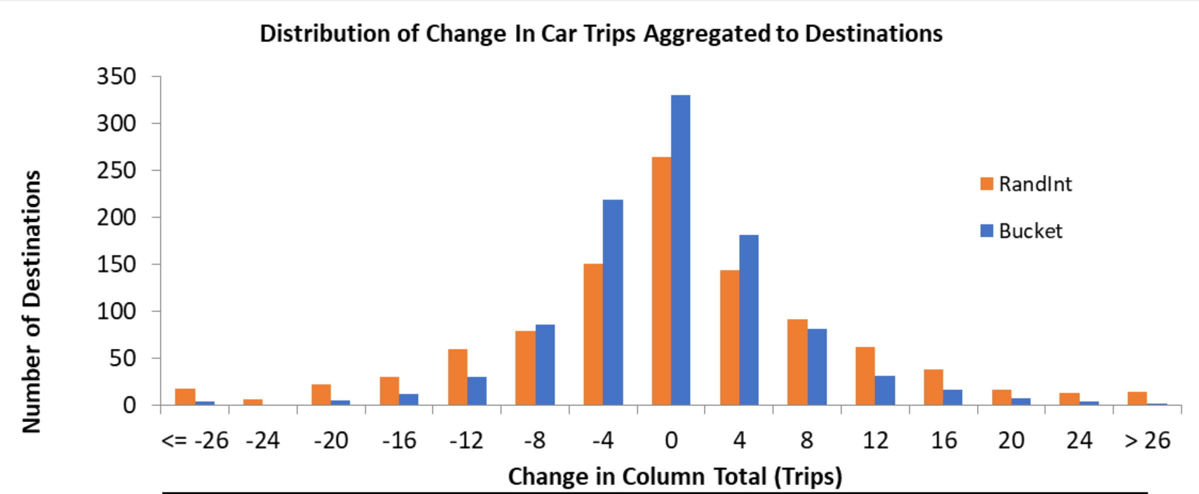


	Stdv	Mean	Skew	RMSE	Sum ABS Error	kurtosis	Max ABS Error
Bucket	0.28	-0.01	0.07	0.06	238.61	-1.09	0.50
RandInt	10.16	-0.50	0.01	2.29	7383.69	1.61	45.58

The difference between Bucket Rounding and Random Integer methods in also obvious in performance metrics. The Bucket Rounding method demonstrates more stable statistics, having lower standard deviations of 0.28 at the origin and 6.67 at the destination compared to 10.16 and 11.65 respectively, and more controlled mean values of -0.01 for both against -0.50 and -0.48.

The bucket rounding method has a lower RMSE, with 0.06 and 1.50 for origin and destination compared to 2.29 and 2.62 in the Random Integer method. Similarly, the Sum of Absolute Errors (SAE) for Bucket rounding stands at 238.61 and 4785.14, much lower than Random Integer's values which are in the thousands, 7383.69 and 7785 for the origin and destination, respectively. Notably, the kurtosis value for the destination using the Random Integer method is high at 8.31 compared to 2.52 with Bucket Rounding, suggesting a higher propensity for outliers. Even though the Random Integer approach tends to offer a slightly better performance in terms of skewness at the origin point, it showcases a tendency for higher absolute errors, with max absolute error figures standing notably higher at 45.58 and 90 compared to Bucket Rounding's 0.50 and 28.28.

Figure 2: Car journey to work matrix destination totals



	Stdv	Mean	Skew	RMSE	Sum ABS Error	kurtosis	Max ABS Error
Bucket	6.67	-0.01	0.11	1.50	4785.14	2.52	28.28
RandInt	11.65	-0.48	-0.92	2.63	7785.00	8.31	90.00

Figure 3 and Figure 4 geographically maps a sample of the residuals of origin and destination matrices for the bucket rounding and random integer method respectively. Geographical distribution of changes appears to be random with no bias. The only difference is the small variations at origin zones in the bucket rounded case which fit with the expectation due to the bucket rounding process controlling matrix row totals.

Figure 3: The difference between bucket rounded matrix and original matrix for car journey to work

A- For origin zones **B- For destination zones**

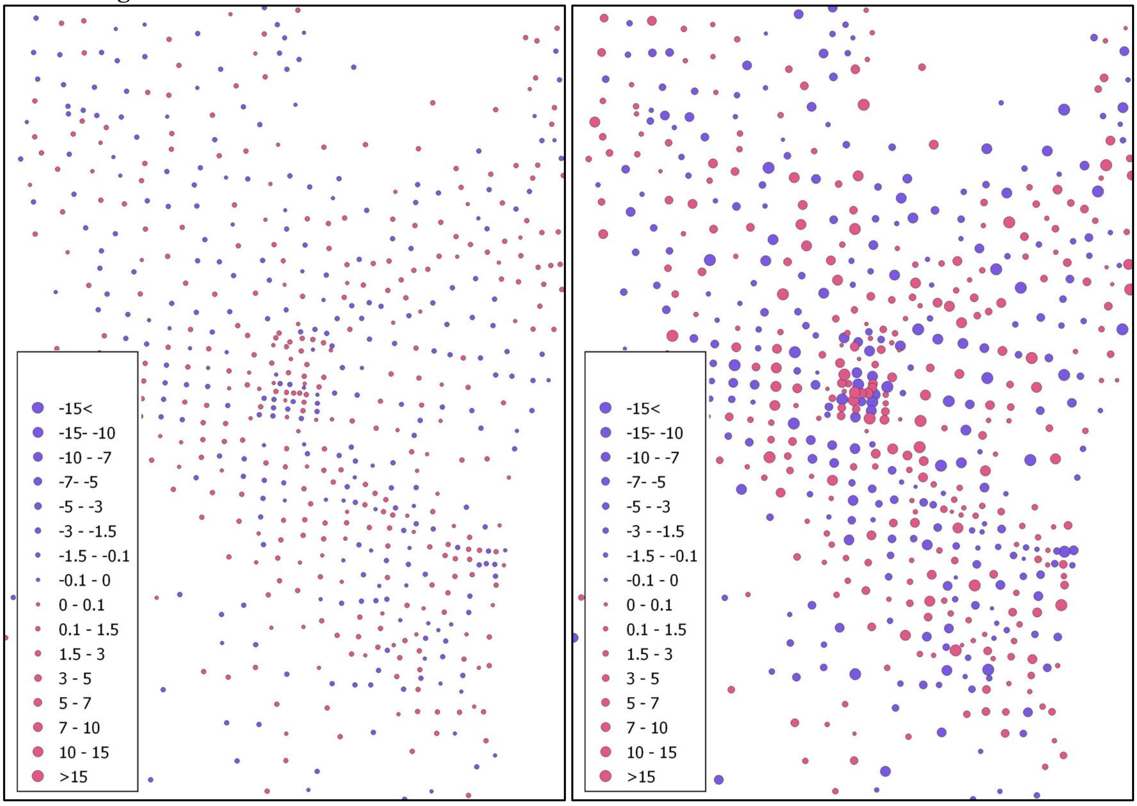


Figure 4: The difference between random integer rounded matrix and original matrix for car journey to work

A- For origin zones **B- For destination zones**

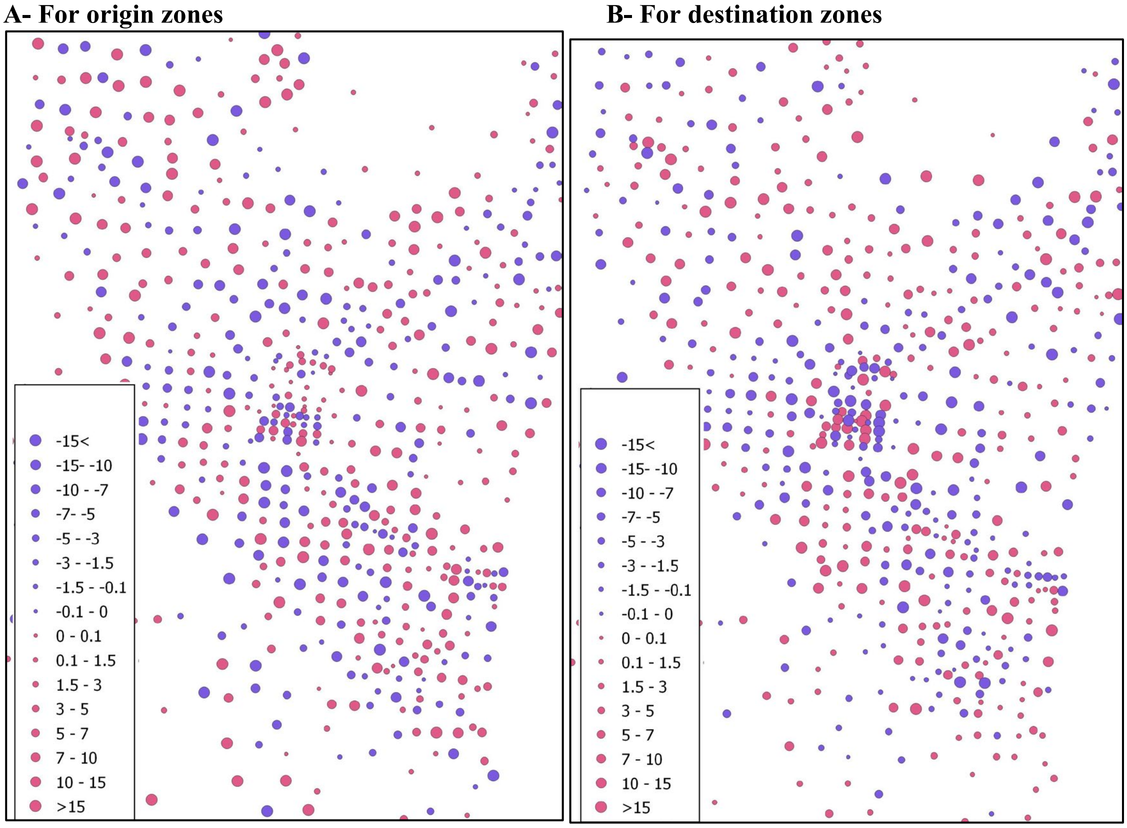
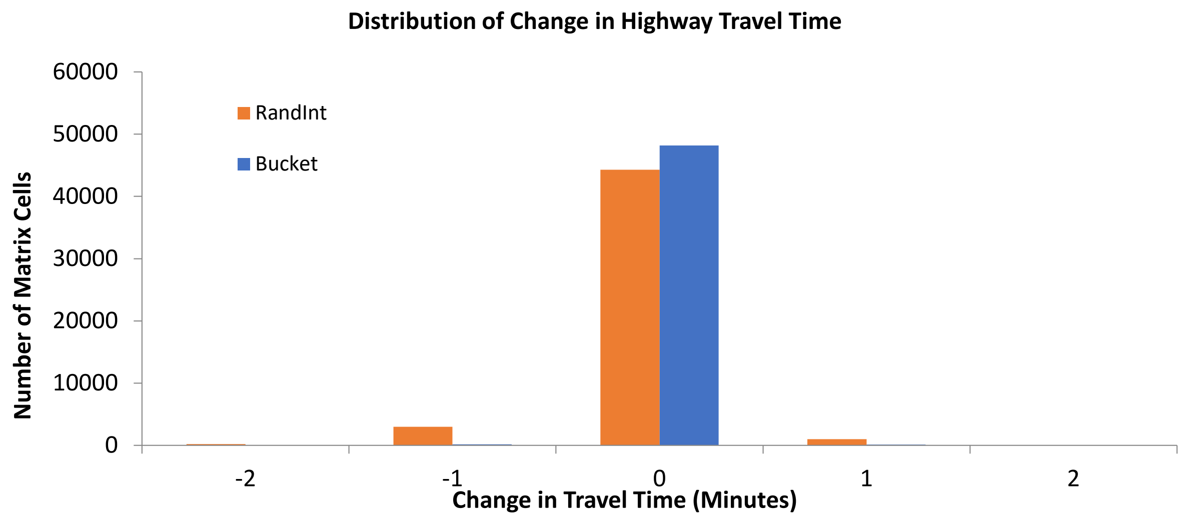


Figure 5 shows comparison of rational demand based and integer demand-based highway time skims at element level. This is a random sample of elements from a matrix and is limited feasible origin to destination cells. The correlation is excellent for both methods of integer demand creation.

This overall pattern affirms that both methods exhibit a pronounced tendency to generate values clustered around a central point. However, the Random Integer method has a somewhat wider spread with a more substantial presence in the outer bins compared to the almost exclusive central focus seen in the bucket rounded method.

The statistical attributes of the histogram depict both the Bucket and Random Integer methods. The Bucket method has a tighter standard deviation of 0.13 compared to 0.33 of the Random Integer method, showcasing more compact data distribution. While both methods are slightly left-skewed, the Random Integer method exhibits a stronger skew with a value of -0.72 compared to the -0.08 of the Bucket method. The Bucket method portrays lower errors with an RMSE and SAE of 0.06 and 4261.36 respectively, as opposed to the Random Integer values of 0.17 and 10159.77. Despite both distributions being leptokurtic, the Random Integer method has a higher kurtosis at 13.11 compared to 10.63 in the Bucket method, hinting at more pronounced peaks and tails than the normal distribution. The Random Integer method also reveals a higher maximum absolute error (3.41) compared to the Bucket method (2.14), implying greater individual variations in its distribution. Overall, the Bucket method seems to maintain a more central data depiction, with lower error metrics relative to the Random Integer method, which shows a broader data dispersion with a mean of -0.07.

Figure 5: Car time skims from original and integer demand

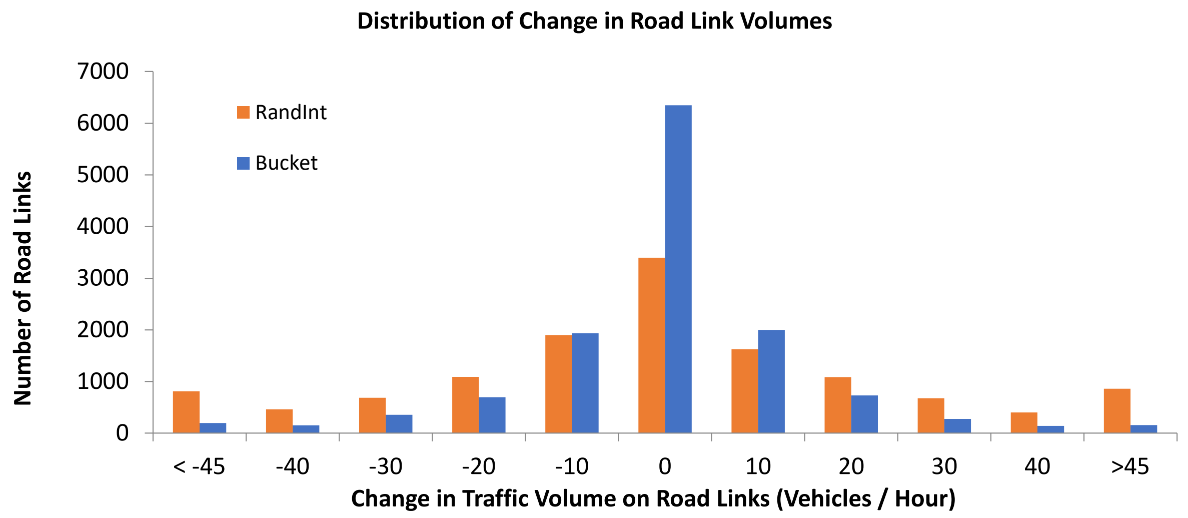


	Stdv	Mean	Skew	RMSE	Sum ABS Error	kurtosis	Max ABS Error
Bucket	0.13	0.00	-0.08	0.06	4261.36	10.63	2.14
RandInt	0.33	-0.07	-0.72	0.17	10159.77	13.11	3.41

Figure 6 shows assigned highway volumes comparing the original demand with each method of Integer demand. The histogram reveals significant differences in the data distribution of the two methods. Observing the bins of distribution, the Bucket method registers a more condensed clustering around the -5 to 5 range. Contrarily, the Random Integer method displays a broader distribution, extending noticeably into the bins below -45 and above 45.

Turning to the detailed statistics, the Bucket method manifests a more stable output with a standard deviation of 17.78 compared to the Random Integer's 33.61. Despite a mean value that is more negative (-0.36) compared to the Random Integer method (-0.02), it has a more narrowed focus of data represented by a high kurtosis value of 43.55. This is corroborated with a lower RMSE value (4.53) and a lesser sum of absolute errors (SAE) at 129099.22, implying a more consistent prediction. Conversely, the Random Integer method exhibits a slight positive skewness of 0.11 and has a larger scatter in data, which is evident from a higher RMSE of 11.06 and a substantial SAE of 280103.16. Furthermore, it tends to produce more extreme values, highlighted by a higher maximum absolute error of 366.78 against 328.53 in the Bucket method. Despite its wider distribution, its kurtosis is less at 9.85, showing a lesser peaky distribution than the Bucket method.

Figure 6: Assigned highway volume comparison at road link level



	Stdv	Mean	Skew	RMSE	Sum ABS Error	kurtosis	Max ABS Error
Bucket	17.78	-0.36	-1.57	4.53	129099.22	43.55	328.53
RandInt	33.61	-0.02	0.11	11.06	280103.16	9.85	366.78

4. Conclusion

In trip based models using Cube Voyager, conversion of real number demand matrices to integer values can reduce assignment run times. This is especially important for large models that require extensive computations and iterate through multiple assignments.

The results from the integer demand assignments tested appear to hold sufficient accuracy for transport planning purposes. For immediate practical applications, the authors have adopted the bucket rounding method to create integer demand. It offers simplicity of implementation, minimum change from original matrix values and the smallest change in assignment outcomes.

It is also a deterministic process that is repeatable. It is acknowledged that the development (numbering) of the zoning system needs to be sensible such that most sequential zones are geographically adjacent. This is viewed by the authors as good practice.

The bucket rounding method clearly and expectedly leads to greater variation for destinations than origins. For future work, the authors recommend experimenting different rounding factors and cell processing orders to see if they affect the results significantly.

The authors have not attempted integer demand assignment in model runs for user benefit estimation analysis. In the bucket rounding process the user cannot control where matrix cell values are rounded up or down. This creates the risk of increasing travel between zone pairs that have increased cost. The result would be unacceptable in origin-destination user benefit analysis.

The authors perceive merit in the random integer approach. Future investigation may indicate:

- How a random integer approach might indicate how much uncertainty exists in strategic model outputs.
- How fixed sets of pseudo random probabilities may usefully control variation between iterations and scenarios, and whether this approach may produce results suitable for user benefit estimation.

References

ALLEN, W. (Multiple dates) Personal verbal discussion.

CHARLESWORTH, O. (2023) email communication (21 Feb 2023 & 17 April 2023)

JANSON, B. N.(1991) ' Dynamic assignment for urban road networks', Transport Res B, 25(2/3), 143–161

OREGON DEPARTMENT OF TRANSPORTATION (2018) 'Alternative Traffic Assignment Methods Framework Report', in: TRANSPORTATION, O. D. O. (ed.) Oregon, USA: State Government of Oregon.

ORTÚZAR, J. D. D., WILLUMSEN, L. G. & ORTÚZAR S, J. D. D. (2011) Modelling transport. Chichester, West Sussex, United Kingdom: John Wiley & Sons.

SAW, K., KATTI, B. & JOSHI, G. (2015) 'Literature review of traffic assignment: static and dynamic', International Journal of Transportation Engineering, 2, pp. 339-347.

SHEFFI, Y. (1985). "Urban Transportation Networks". Prentice-Hall, Englewood Cliffs, NJ.