

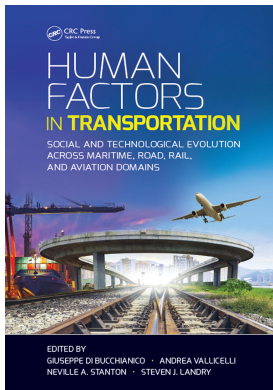
This article was downloaded by: 10.2.97.136

On: 31 May 2023

Access details: *subscription number*

Publisher: *CRC Press*

Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: 5 Howick Place, London SW1P 1WG, UK



Human Factors in Transportation Social and Technological Evolution Across Maritime, Road, Rail, and Aviation Domains

Giuseppe Di Bucchianico, Andrea Vallicelli, Neville A. Stanton, Steven J. Landry

Telematics, Urban Freight Logistics, and Low Carbon Road Networks

Publication details

<https://test.routledgehandbooks.com/doi/10.1201/9781315370460-22>

Giuseppe Di Bucchianico, Andrea Vallicelli, Neville A. Stanton, Steven J. Landry

How to cite :- Giuseppe Di Bucchianico, Andrea Vallicelli, Neville A. Stanton, Steven J. Landry. 25 Aug 2016, *Telematics, Urban Freight Logistics, and Low Carbon Road Networks* from: *Human Factors in Transportation, Social and Technological Evolution Across Maritime, Road, Rail, and Aviation Domains* CRC Press

Accessed on: 31 May 2023

<https://test.routledgehandbooks.com/doi/10.1201/9781315370460-22>

PLEASE SCROLL DOWN FOR DOCUMENT

Full terms and conditions of use: <https://test.routledgehandbooks.com/legal-notices/terms>

This Document PDF may be used for research, teaching and private study purposes. Any substantial or systematic reproductions, re-distribution, re-selling, loan or sub-licensing, systematic supply or distribution in any form to anyone is expressly forbidden.

The publisher does not give any warranty express or implied or make any representation that the contents will be complete or accurate or up to date. The publisher shall not be liable for an loss, actions, claims, proceedings, demand or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.

18

Telematics, Urban Freight Logistics, and Low Carbon Road Networks

Guy Walker and Alastair Manson

CONTENTS

18.1	Introduction	225
18.1.1	Telematics.....	225
18.1.2	Street Patterns and Network Types.....	226
18.1.3	Network Metrics	226
18.1.4	The Problem.....	228
18.2	Method	229
18.2.1	Design.....	229
18.2.2	Real-Life Urban Networks.....	229
18.2.3	Development of Network Models	231
18.2.4	Vehicle Types.....	232
18.2.5	Network Demand	233
18.3	Results and Discussion	233
18.3.1	Telematics versus Journey Duration	235
18.3.2	Telematics versus Journey Length.....	236
18.3.3	Telematics versus Journey Cost	236
18.3.4	Telematics versus Carbon Emissions	237
18.3.5	Optimization Values.....	238
18.3.6	Fundamental Relationships.....	239
18.4	Conclusions.....	240
	Acknowledgment.....	241
	References.....	241

18.1 Introduction

18.1.1 Telematics

Eighty percent of the UK population now lives in an urban area. This drives increasing urban freight movements which, in turn, interact with dense street networks and a strong planning incentive to maximize their capacity and reduce vehicle emissions (Hesse and Rodrigue, 2004). Telematics, in the form of route guidance, is a key enabler for this. There is good evidence for the positive benefits telematics can have (e.g., Asvin, 2008; Dutton, 2011; Giannopoulos, 1996, etc.) but as this technology continues along the s-curve toward full market saturation there are some fundamental questions that still need to be explored. Are some urban road network topologies more energy efficient when paired with telematics

technology than others? If so, to what extent might it influence a telematics strategy? Do all drivers have to have complete knowledge of traffic conditions? How realistic is this assumption anyway? Is it safe to assume that having invested in telematics drivers will adhere to route guidance information in all cases? Research (e.g., Bonsall, 1992; Bonsall and Palmer, 1999; Chorus et al., 2006; Karl and Bechervaise, 2003; Lyons et al. 2008, etc.) shows that between 30% and 50% of drivers do not: what happens then? Clearly, the success of telematics technology is heavily contingent on factors like these and this study provides an initial exploration.

18.1.2 Street Patterns and Network Types

Conventional transport network analysis methods use planar representations to reduce a complex transport network into a set of fundamental elements: nodes that represent junctions and links that represent roads (Lowe, 1975). A two-dimensional set of systematically organized points and lines like this are referred to as a planar graph. These are the basis upon which various forms of spatial analysis normally proceed (e.g., Bowen, 2012; O'Kelly, 1998). As for urban centers themselves, these tend to evolve as a product of the area's rate of growth, period of formation, location, topography, climate, culture, and so on (Thomson, 1977). Planar graphs of street patterns reveal this individuality, as do the large number of descriptive terms applied to them (Table 18.1).

A long-standing goal in telematics research has been to define certain road network "typologies" (e.g., Reggiani et al., 1995), a task made more difficult by the inconsistent use of terms/concepts such as those shown in Table 18.1. Despite this, however, it is possible to discern a much smaller recurring subset of network patterns. Brindle (1996) argues for as few as two "fundamental" urban street layouts, the grid and the tributary. Table 18.1, however, concurs with the work of Marshall (2005) in which four archetypal street patterns can be identified: the linear, tributary, radial, and grid patterns (as shown in Figure 18.1).

18.1.3 Network Metrics

Network diagrams provide a visual representation that, in simple cases, makes it very easy to discern one archetype from another. In more complex real-world examples, the visual complexity makes this task difficult to perform reliably and objectively. In these cases it is possible to turn to a number of formal metrics drawn from graph theory. These enable the connectivity of street patterns to be calculated. Three metrics, the Beta Index, the Gamma Index and network depth, are used for this purpose.

The Beta Index is a simple equation used to determine the relationship between the total number of links and the total number of nodes in a network and is calculated using the following equation:

$$\beta = e/v$$

where e is number of links, v number of nodes and $0.5 < \beta < (v - 1)/2$.

The Beta Index provides a measure of linkage intensity or "the number of linkages per node" (Lowe, 1975). Beta values generally lie between 0.5 and 3, with networks of values >1 consisting of some of the nodes within the network having more than one route between them and the network being considered well connected. Beta values <1 indicate that the network is not as well connected, there being only one route between nodes.

TABLE 18.1

Descriptive Terms Applied to Urban Street Patterns

Author	Descriptive Terms
Unwin (1920)	Irregular
	Regular
	Rectilinear
	Circular
	Diagonal
	Radiating lines
Moholy-Nagy (1969)	Geomorphic
	Concentric
	Orthogonal connective
	Orthogonal modular
	Clustered
Lynch (1981)	Star (radial)
	Satellite cities
	Linear city
	Rectangular grid cities
	Baroque axial network
	The lacework
	Other grid (parallel, triangular, hexagonal)
	The “inward” city (medieval, Islamic)
	The nested city
	Current imaginings (megaform, bubble floating, underground, etc.)
Sato (1998)	Warped grid
	Radial
	Horseback
	Whirlpool
	Unique structures
Frey (1999)	The core city
	The star city
	The satellite city
	The galaxy of settlements
	The linear city
	The polycentric net

Source: Marshall, S., *Streets and Patterns*, Spon Press, Oxon, 2005.

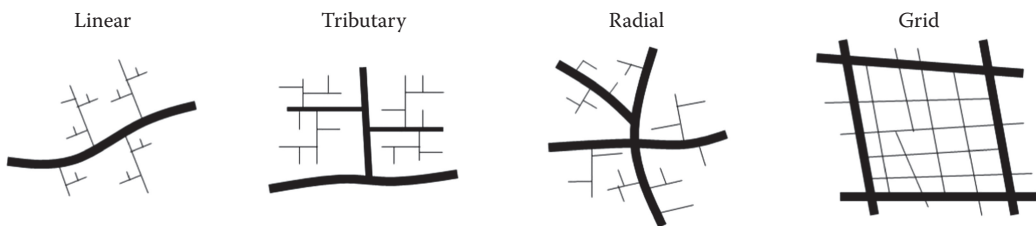


FIGURE 18.1
Urban street pattern archetypes.

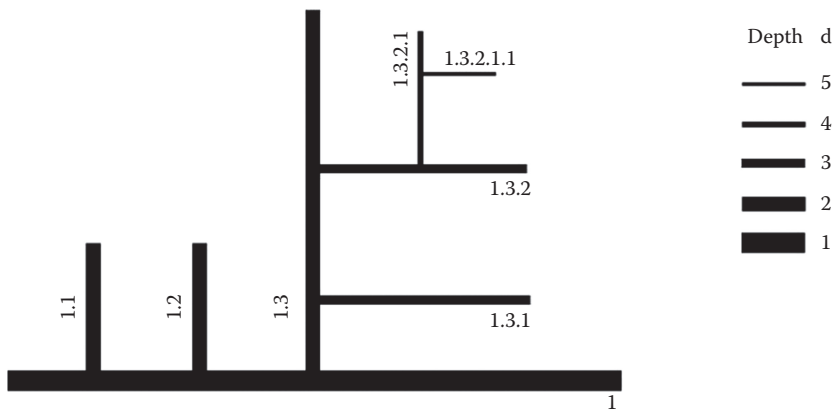


FIGURE 18.2

An example of what is meant by the “depth” of a network, with the major route being represented as the thickest line and the minor routes being represented with the thinnest line.

The “Gamma Index” helps to identify “the ratio between the actual and the maximum possible number of links” in the network (Lowe, 1975). This essentially determines whether or not every node is connected by a link, and is derived from the following equation:

$$\gamma = e / (3(v - 2))$$

where e is number of links, v number of nodes and $0 < \gamma < 1$.

For example, if $\gamma = 0.5$, this means that only 50% of the maximum possible number of links in a network are provided and that all of the nodes are not fully connected.

The “depth” of a network is a relatively simple concept. In essence, it accounts for the relative distance between the most minor route and the most major route. It establishes the idea of a hierarchy and the different interconnections that exist between levels. For example, minor roads providing access to houses are “deep” whilst major routes are “shallow.” An example of this is shown in [Figure 18.2](#) where the thinner the link, the deeper the road. This particular network, taken from Marshall (2005), demonstrates that the network has a depth of five which is a deep level of penetration and results in potentially more links being provided between origins and destinations.

Network depth is important if the goal is to impartially compare different street patterns. If one network was to have a depth of four and another a depth of two, the so-called deeper network would have more connectivity. This would allow the road user to travel between points in a shorter period of time as there would be more route choice options for a road user to exploit. Different street patterns (with different Beta and Gamma coefficients) can be legitimately compared if the network depth is kept constant.

18.1.4 The Problem

Abstracting street patterns to the level of planar networks puts them on the same level as communications and other network types, for which there is a rich literature in the fields of graph theory (Harary, 1994), sociometry (Leavitt, 1951; Monge and Contractor, 2003), and complexity (Watts and Strogatz, 1998). We know from this literature that network type is a strong contingency factor in how they perform (Leavitt, 1951; Pugh et al., 1968; Watts and

Strogatz, 1998, etc.). This is in opposition to the tacit theories underlying telematics, which tend to assume that more technology, more route guidance, and the greater the driver's knowledge of the wider traffic conditions, the better the network will perform (Nijkamp et al., 1997). We know from the wider literature on communication networks that this is not necessarily the case. Of course, roads are not communications networks in the way they have been previously studied, so in order to explore the hypothesis that street pattern is an important contingency factor in the benefits to be accrued from telematics technology, we apply instead an agent modeling approach called traffic microsimulation. Microsimulation enables us to create a set of virtual street layouts based on real towns and cities, populate them with virtual traffic having differing levels of telematics, and observe the outcomes in terms of journey length, duration, cost, and, most importantly, carbon emissions. This is an exploratory study aimed at discerning the direction of the observed effects, and using this to propose different telematics strategies and guidance.

18.2 Method

18.2.1 Design

The study uses traffic microsimulation to test the interaction between different levels of vehicle telematics and the outcomes achieved within different street patterns. There are four dependent variables: journey duration, journey length, journey cost, and carbon output. These dependent variables are contingent upon two independent variables: driver knowledge of the traffic conditions in the network provided by telematics, and street pattern type. Driver knowledge had three levels. Hundred percent telematics represented urban delivery vehicles in which every driver had complete knowledge of the traffic conditions on the network and was required to act upon the guidance given (a "best-case" telematics implementation). Fifty percent telematics represented other non-freight vehicles in the network equipped with telematics/route guidance/sat nav, etc. but which, in accordance with the literature, only complied with/took notice of 50% of the information provided. Zero percent telematics represented vehicles with no telematics, with the drivers having only immediate local knowledge of traffic conditions based on what they can see. Street pattern had four levels: linear, radial, grid, and tributary. The street patterns were based on real urban locations, with network depth held constant in order to control for nonsystematic biases in connectivity. Network demand was based on real-life traffic count data from the relevant sites.

18.2.2 Real-Life Urban Networks

As determined in the previous section, there are four common forms of urban transport network layout: linear, radial, grid, and tributary. It was necessary to develop microsimulation models which closely reflect the layouts of these urban networks and it was considered important to relate the layouts to real-life towns and cities. This gives a more realistic approach and a more credible set of results. The Beta and Gamma coefficients were used to calculate the connectivity of the network archetypes shown in [Figure 18.1](#) in order to select real-life road networks exhibiting the same properties. This approach allows networks to be categorized by a visual and a statistical approach. The depth of each model was set to three in order to control for the effects of network magnitude.

The linear network required locating a small town in which there is one main road with the town located along its length. A settlement identified as meeting these criteria is Aviemore, a town located in the Scottish Highlands. The radial network is one that has several roads intersecting or converging at a center, analogous to the spokes of a bicycle wheel. These features can often be found in a larger town which has been formed at a crossroads. These criteria are met by Dalkeith, a town located just to the south of Edinburgh. The grid network, as its name suggests, is a network with straight roads intersecting other straight roads at right angles to form a collection of squares or blocks. The characteristics of this network type are found in the center of Glasgow. Finally, the tributary network is analogous to tributary rivers, with the smaller rivers feeding the bigger rivers. In road networks, it is the small roads that connect to the larger roads with “network depth 1” only connecting to “depth 2” and “depth 2” only connecting to “depth 3,” and so on. The result of this is that only the shallower roads are busy and the deeper roads are not used as shortcuts. An area meeting the description of a tributary network is Livingston, a so-called “new town” in central Scotland. Planar graphs of these real-life street networks are shown in Figure 18.3.

Beta and Gamma values are calculated for each of the real-life towns to check the extent to which they conform to the linear, radial, grid, and tributary archetypes, as shown in

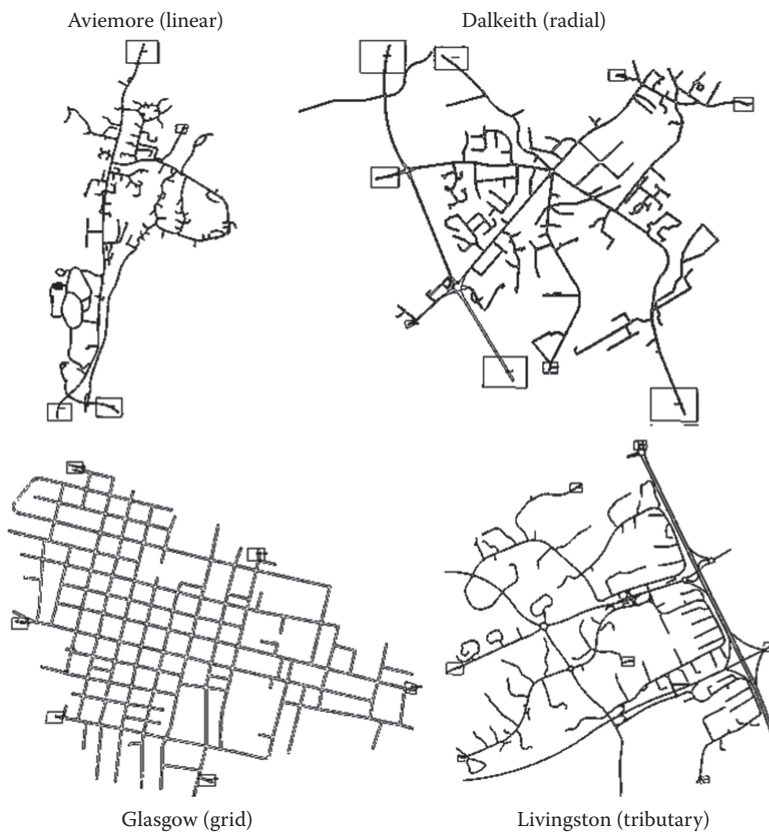


FIGURE 18.3

Traffic microsimulation models of Aviemore (tributary), Dalkeith (radial), Glasgow (grid), and Livingston (tributary).

TABLE 18.2

Values Obtained for Beta and Gamma for the Standard Layouts Shown in [Figure 18.4](#)

	Network	Nodes (v)	Links (e)	Beta	Gamma (%)
Archetype	Linear	19	35	1.84	69
Real Life	Aviemore	140	257	1.84	62
Archetype	Radial	32	65	2.03	72
Real Life	Dalkeith	140	268	1.91	65
Archetype	Grid	33	73	2.21	78
Real Life	Glasgow	140	278	1.99	67
Archetype	Tributary	9	17	1.89	81
Real Life	Livingston	140	265	1.89	64

Table 18.2. The real-life networks are considerably larger than the archetypes yet it can be noted how the network metrics align, showing how the underlying network structures are equivalent in type if not size. The Beta values for the linear and Aviemore networks, for example, are exactly equal as are the Beta values for the tributary and Livingston networks, where differences do exist (and they are relatively modest), the rank order of the network types is still preserved.

18.2.3 Development of Network Models

Planar graph representations of Aviemore, Dalkeith, Glasgow, and Livingston were extracted from ArcGIS (a mapping and spatial analysis software) and imported into S-Paramics (the traffic microsimulation software) in order to create a basic model of each. An attempt was made to ensure the modeled network was as true to life as possible but some simplifications were required in order to isolate the effects of street patterns and

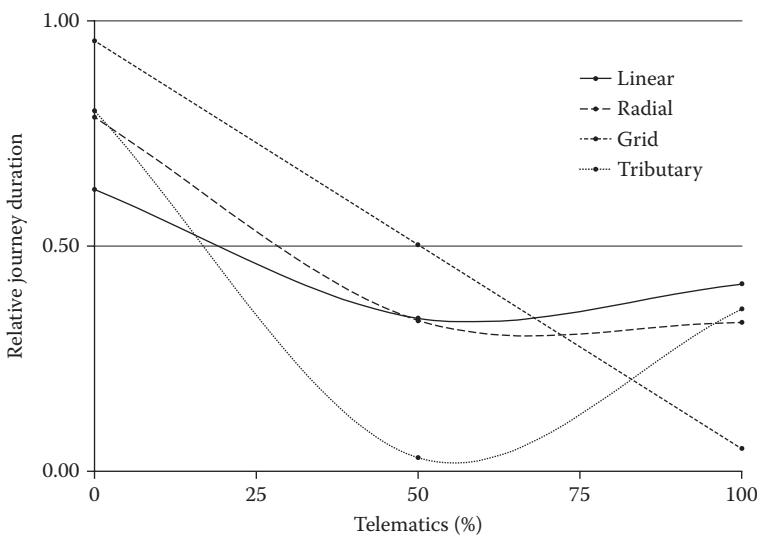


FIGURE 18.4

Interactions between street pattern, driver knowledge of network conditions provided by vehicle telematics, and relative journey length. A 100% telematics represents urban freight vehicles.

route guidance from specific and localized variations in the traffic situation. As such, junctions had simple priorities applied with the bigger roads having priority over the smaller roads. Traffic lights were avoided all together. There were also no buses or bus routes applied as not all networks had buses arriving at similar times and some networks had bus lanes whereas others did not. A number of steps were taken to calibrate the models to the real-world context despite these simplifications being applied. A number of parameters in the model were adjusted to ensure this. First, the signpost distance refers to the distance ahead of a hazard at which the modeled road users become aware of it, and was standardized to 80 m to allow the traffic to use both lanes of the entrances and exits of roundabouts (anomalous behavior would arise if not). Visibility was also varied. This relates to how far back from the stop-line vehicles begin assessing their gap distance. This ensured that vehicles approaching roundabouts continued onto it in situations where nothing was coming and stopped in cases where something was approaching. The distance which meant vehicles followed this rule was found to be 20 m. These rules allowed more life-like driver behavior to be represented, and for a good approximation of the traffic situation actually experienced in these locations to emerge. These steps were applied consistently across all the networks in order to isolate the effects of network and vehicle type.

18.2.4 Vehicle Types

The principle vehicle-based manipulation was the amount of knowledge drivers had of wider network conditions based on the amount of route guidance provided. Three levels were implemented:

- Vehicle type 1 (urban delivery vehicle) had 100% knowledge of traffic conditions on the network via telematics and followed the route guidance information they were given 100% of the time.
- Vehicle type 2 (private car) had 100% knowledge of traffic conditions on the network via telematics but only chose to follow it 50% of the time (ignoring the other 50%).
- Vehicle type 3 (private car) had no telematics or route guidance and therefore the drivers had 0% knowledge of traffic conditions on the network beyond what they could see ahead of them.

The three levels of telematics/route guidance were implemented in the microsimulation model by manipulating feedback. Feedback is information supplied to the road user, via telematics, about current network conditions. Specifically, it lets them know of journey times on all routes so they can decide an optimum route to choose. Feedback is calculated using two aspects, the feedback interval and the feedback factor. Both were adjusted in such a way as to give rise to realistic driver behavior. The feedback interval refers to how often the information is updated and an interval of 2 min was used. This is a common value in similar models and avoids the modeled drivers making unrealistically rapid and unstable route choice decisions. The feedback factor is concerned with what percentage of delay information is taken from the previous feedback interval and was taken to be 0.5% or 50% as standard. A perturbation level of 5% was applied to all three vehicle types. This helps to account for variability in travel costs, or a driver's perception of these travel costs. As perturbation increases, the road users' concentration tends to focus more on reducing journey cost. However, by applying a small percentage it means that road users will continue to focus on reducing journey length and journey duration as the key variants but will also look to reduce their cost simultaneously.

The same mix of traffic was applied to all the networks in order to capture the interaction between “normal traffic” and urban freight delivery vehicles. Fifty percent of the road users in all the network types were “vehicle type 3” (0% telematics) with the remaining 50% being split into two: 25% of road users were “vehicle type 2” (50% telematics) and 25% of road users were urban delivery vehicles, or “vehicle type 1” (100% telematics). The normal traffic (i.e., vehicle types 2 and 3) were modeled as medium-sized saloon cars, whereas the urban delivery vehicles (i.e., vehicle type 1) were modeled as car-based vans. This is (a) because larger vehicle types would give unfavorable differential effects on networks that are less suitable for larger vehicles and (b) the literature identifies vans as the “dominant mode” in these contexts (e.g., Cherrett et al., 2012).

18.2.5 Network Demand

The demand profile controls the number of vehicles in the network, the origin and destination of the vehicles, the percentages of vehicle type and the release rate of vehicles into the network. The number of vehicles released from the origin to the destination was varied from model to model based on actual traffic count data. The goal was to bring each network to its peak PM traffic flow and hold it there for the duration of the study. To do this, peak PM values from the nearest traffic counter site (Scottish Government, 2012) were used and multiplied by 24. This total value was then split evenly between each of the origins and destinations. The release rate of the vehicles over the 24-h period was constant so that all the vehicles were not released at once and a steady flow was maintained. Each model was then subject to 30 “batch runs” between the network model hours of 1600 and 2000, which was the length of the peak PM flow period. The models had, of course, been established in this peak flow state for many hours previously hence any transient effects of the model being initially loaded with traffic were avoided. These 30 runs allowed a significant amount of data to be obtained on the outcome variables of journey duration, length, cost, carbon output, and their contingency on network type.

18.3 Results and Discussion

The output from running the S-Paramics microsimulations is a set of raw data for each individual vehicle as it progressed through the network. The software also calculates the position of each individual vehicle every half second and records its coordinates against time. This data was passed through an external programme known as “AIRE” which calculated the resulting pollution output of each individual vehicle for a specific year, which was chosen to be 2012. An average value for carbon output was obtained for each vehicle type, along with data on journey duration, length, and cost. A summary of the uncorrected average and standard deviation values obtained from the simulations is provided in [Table 18.3](#). [Table 18.4](#) shows the same results corrected for network size/distance, collapsing some of the key variables into average speed, cost per km, carbon output in g/km, and total emissions.

The values shown in [Table 18.3](#) are absolute, in that no correction is made for the differing sizes of the networks. The values in [Table 18.4](#) are corrected, and provide a number of key insights. Ignoring vehicle telemetry for a moment, it can be noted that the linear and radial networks are very similar, both being able to support average speeds in the region of 42 km/h, costs per km of approximately 27 pence, with vehicles on the network

TABLE 18.3

Summary of the Uncorrected Journey Length, Duration, Cost, and Carbon Output Data Obtained from the Modeled Networks

	Vehicle Type	Journey Length (m)		Journey Duration (s)		Journey Cost (Pence)		Carbon Output (g)	
	Telematics	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Linear	0%	2152.7	30.7	183.3	2.4	224.6	1.6	130.0	1.8
	50%	2155.3	51.6	182.7	4.0	225.2	2.5	128.5	2.9
	100%	2165.8	44.2	182.8	3.4	226.0	2.6	128.1	2.7
	Mean	2157.9		182.9		225.3		128.9	
Radial	0%	2286.4	10.5	194.6	0.8	198.8	0.8	137.7	0.8
	50%	2281.2	16.9	193.7	1.3	198.2	1.1	137.2	1.3
	100%	2285.8	17.5	193.7	1.3	198.9	1.1	137.2	1.1
	Mean	2284.5		194.0		198.6		137.4	
Grid	0%	1304.6	6.3	147.5	0.8	124.2	0.6	129.0	0.9
	50%	1316.3	9.5	142.5	1.3	124.2	0.9	122.1	1.3
	100%	1326.9	12.2	137.5	1.2	124.0	1.0	115.0	1.0
	Mean	1315.9		142.5		124.1		122.0	
Tributary	0%	3662.4	16.2	309.8	1.2	321.5	1.6	214.5	1.0
	50%	3654.8	28.7	309.0	2.4	320.6	2.9	213.8	1.6
	100%	3663.6	26.0	309.4	2.2	321.4	2.9	214.4	1.9
	Mean	3660.3		309.4		321.2		214.2	

TABLE 18.4

Summary of Corrected Speed, Cost, and Carbon Output Data

	Vehicles		Speed	Cost	Carbon		
	Total N	Telematics	km/h	Pence/km	g/km	Total kg	
Linear	3000	0%	42.28	28.05	60.39	390.00	
		50%	42.47	27.66	59.62	385.50	
		100%	42.65	27.31	59.15	384.32	
		Mean	42.47	27.67	59.72	1159.82	Total
Radial	4752	0%	42.30	26.34	60.23	654.40	
		50%	42.40	26.34	60.14	651.93	
		100%	42.48	26.26	60.02	651.95	
		Mean	42.39	26.32	60.13	1958.28	Total
Grid	6000	0%	31.84	75.79	98.88	773.99	
		50%	33.25	70.47	92.76	732.60	
		100%	34.74	65.32	86.67	690.02	
		Mean	33.28	70.53	92.77	2196.61	Total
Tributary	5995	0%	42.56	15.99	58.57	1285.97	
		50%	42.58	16.00	58.50	1281.77	
		100%	42.63	15.97	58.52	1285.29	
		Mean	42.59	15.99	58.53	3853.03	Total

each emitting approximately 60 g/km of carbon. The tributary is the same aside from cost, which is the lowest of all the road networks at 15.99 pence/km. The slowest (33.28 km/h), most expensive (70.53 pence/km), and carbon intensive (92.77 g/km) network is the grid but it is within this network that the urban delivery vehicles (with 100% telemetry) performed the best. In this situation telemetry is raising average speeds by 2.9 km/h, reducing costs by a not insignificant 10.47 pence/km and, most importantly, reducing carbon emissions by 12.21 g/km. The carbon value is of course determined by the physical size of the networks and the journey lengths therein, so in these examples the larger tributary network (i.e., Livingston) has the highest total emissions (3.8 tonnes of carbon per modeled peak PM), however, the network with the shortest average journey lengths (i.e., Glasgow/grid) has the second worst carbon outputs (2.2 tonnes).

There are smaller differential effects present in the other network types that are also important. Although smaller at the level of individual vehicles, when multiplied by the number of vehicles in the networks (several thousand) and the number of times peak PM hour conditions occur (every weekday evening), these differences begin to magnify significantly. For example, in the tributary network, a per-vehicle difference in carbon emissions of only 0.7 g as a result of telematics still multiplies to an additional daily peak PM carbon output of approximately 4.2 kg, or approximately 1 tonne per year. Multiplied again by the number of settlements with tributary street patterns, these initially marginal differences start to accumulate rapidly. With this in mind, the following sections shift the focus from absolute values to relative values in order to discern the direction of these various effects, and what they might mean for an overall telematics strategy.

18.3.1 Telematics versus Journey Duration

In order to provide a visually tractable representation of how the data is behaving, and show the relationships for each network on the same graph, it is necessary to convert absolute values to relative values. These were determined by finding the difference between the actual value and the minimum value and dividing this by the difference. This, therefore, shows the direction of the relationships between road network type and how different levels of vehicle telematics within it perform.

Figure 18.5 shows the relationship between different levels of telematics and the relative journey duration experienced by each type of road user for each of the four models. The graph shows that urban delivery vehicles (with 100% telematics) operating within linear and tributary road networks are worse off than “normal traffic” with 50% knowledge/acceptance of route guidance information, albeit not as bad as the population of vehicles with no telematics. Indeed, the results show that the same outcomes on journey duration are achieved at both 100% telematics penetration and approximately 20%, the difference being that the latter is considerably more costly than the former. The trend line obtained for the “radial” network only slightly differs from the “linear” and “tributary” networks in respect of the duration increasing between 50% and 100%, and leveling off thereafter. This shows there is no further benefit of telematics in this context. The relationship for the linear, radial, and tributary networks seems to show that there is an optimum level of knowledge about the traffic conditions on the network. For the optimization of journey durations, a level of knowledge consistent with 100% telematics is not required. This principle does not hold for the “grid” network. Here the trend line shows increasing benefits as more telematics is provided, reaching a maximum benefit at 100% telematics penetration. The broader principle to be extracted here is that 50% knowledge of the traffic conditions on the network are optimum for networks characterized by one or two critical

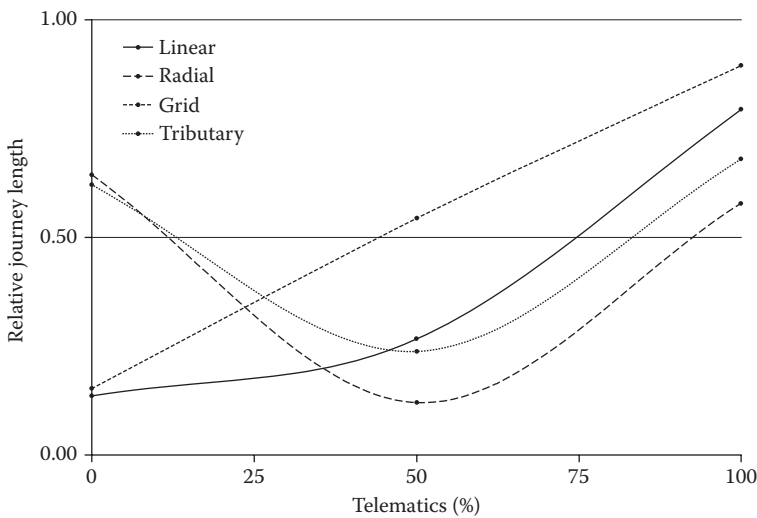


FIGURE 18.5

Interactions between street pattern, driver knowledge of network conditions provided by vehicle telematics, and relative journey duration. A 100% telematics represents urban freight vehicles.

routes between the majority of the origins and destinations. Hundred percent telematics penetration reduces journey durations in networks where there are a large range of routes available to the road user. In this study, urban freight vehicles with 100% telematics extract maximum journey time benefits in grid networks.

18.3.2 Telematics versus Journey Length

Figure 18.2 shows how the journey length taken by road users relates to the amount of telematics each vehicle has, but is contingent on street pattern type. In the linear network, the journey length increases at a slow rate between 0% and 50% telematics penetration before it increases at a much greater rate between 50% and 100%. This relationship is very different from the radial and tributary networks, which both have a long journey length for road users with 0% but falling markedly between 0% and 50% before rising again very steeply between 50% and 100%. As with the results for journey duration, there is an optimum level of telematics for radial and tributary networks (around 50%), with the same network performance achieved at 0% telematics penetration as achieved at 100%. Urban delivery vehicles with 100% telematics would see little benefit in these settings. The grid network differs again. The diagonal line traced through the chart shows that the greater the level of telematics, the greater the journey length as road users exploit the more numerous opportunities to divert. Taken together, Figures 18.2 and 18.5 suggest that shorter journey durations are achieved with longer journey lengths. The broader principle to be extracted here is that urban freight vehicles in networks with more than one route between the origin and destination travel a greater distance but in a shorter time.

18.3.3 Telematics versus Journey Cost

Figure 18.6 shows that the linear network has a more or less direct relationship between telematics-mediated knowledge of network conditions and journey cost (i.e., a straight

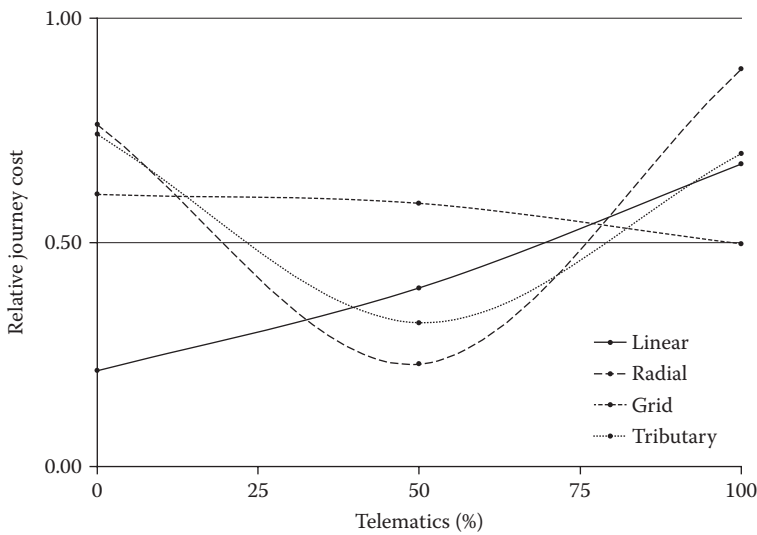


FIGURE 18.6

Interactions between street pattern, driver knowledge of network conditions provided by vehicle telematics, and relative journey cost. A 100% telematics represents urban freight vehicles.

line). It shows that as the acceptance of telematics information increases from 0% to 100%, the journey cost also increases. Interestingly, then, in this network type 0% telematics penetration is the optimum value for cost to be optimized. This is not the case for radial and tributary networks. Both of these undergo a reduction in cost between 0% and 50% with an increase then occurring between 50% and 100%. Once again, the optimum level of telematics penetration in a radial or tributary network is 50%, with further increases not only having a negative effect on journey cost but 100% telematics penetration (as per the urban freight vehicles) yields the same outcome as 0%. The grid network again performs differently to the other three network types. The relationship is linear (i.e., a straight line) between 0% and 50% telematics penetration, before tailing off slightly as 100% telematics penetration is reached. What this means is that 100% telematics penetration is required in grid networks for meaningful journey cost savings to emerge, 0% for linear networks and 50% for radial and tributary networks.

18.3.4 Telematics versus Carbon Emissions

The crux of the analysis is to see what effect these contingent values of journey length, duration, and cost ultimately have on carbon emissions. [Figure 18.7](#) presents the results of this analysis. It can be seen that the linear, radial and tributary networks all follow a similar trend, with carbon emissions decreasing rapidly between 0% and 50% telematics but with varying levels of diminishing further benefits as the telematics rate approaches 100%. The linear and radial networks level off beyond 50%, suggesting little (if any) further benefits of increasing telematics penetration. The results suggest that the carbon emissions from the tributary network worsen with increases beyond 50% telematics penetration. The grid network is once again quite distinct. It contains a directly proportional relationship between telematics penetration and carbon emissions, with the maximum value occurring at 0% and the minimum value at 100%. If reducing carbon emissions are the goal of urban

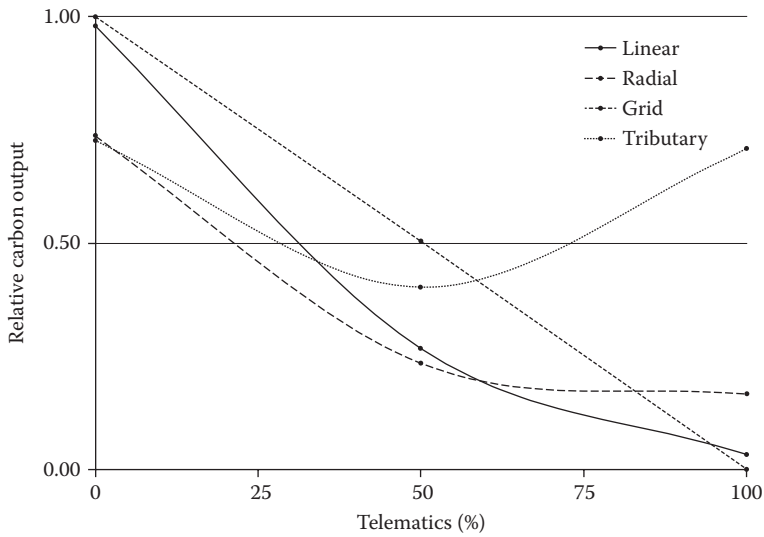


FIGURE 18.7 Interactions between street pattern, driver knowledge of network conditions provided by vehicle telematics, and relative carbon output. A 100% telematics represents urban freight vehicles.

freight vehicles, then telematics has the biggest role to play in grid networks, and apart from tributary networks, there are some benefits to be extracted before 100% telematics is achieved.

18.3.5 Optimization Values

Based on the data and relationships obtained from the previous sections, particularly Figures 18.6 through 18.8, it is possible to create Table 18.5 to show the potential network performance trade-offs involved in minimizing carbon emissions using telematics. A mean level of driver knowledge of network conditions (or acceptance thereof) is given, this representing a simple value by which the best compromise of journey duration, length, cost, and carbon variables is achieved.

Table 18.5 shows that, in theory, urban street networks can be designed to be sustainable with the smallest pollution outputs, designed to reduce the journey duration of road users traveling through them, or designed to reduce traveler costs. In practice, however, street networks have evolved and cannot be changed on the scale necessary to optimize

TABLE 18.5 Optimum Levels of Telematics Penetration for Journey Duration, Length, Cost, and Carbon Emissions for Linear, Tributary, Radial, and Grid Street Patterns

Network	Duration (%)	Length (%)	Traveler Costs (%)	CO ₂ (%)	Mean (%)
Linear	50	0	0	100	38
Radial	50	50	50	100	63
Grid	100	0	100	100	75
Tributary	50	50	50	50	50

these factors. This is where telematics comes in. Telematics interacts with network types to modify their inherent performance. The interaction is not a simple one. It is contingent on the level of telematics information provided to, and accepted by, drivers combined with the topology of the network itself. Where some networks require varying values of telematics penetration to optimize various aspects of the network, some run at the optimum level for the majority of characteristics under one level of telematics. This can be seen in Table 18.5 with the tributary and radial networks, which both run at their most efficient levels for all four characteristics with a 50% telematics rate. The table also shows that for a grid network, 100% telematics penetration is the optimum value. Linear networks, however, do not reach their optimum level of efficiency for any one level of telematics. Table 18.5, therefore, becomes a useful tool when attempting to design a telematics strategy in order to modify the inherent characteristics of urban road networks. Stated simply, some levels of driver knowledge of network conditions (provided via telematics) are more optimal than others, and it depends on the street pattern urban delivery vehicles are operating within.

18.3.6 Fundamental Relationships

The results shown and discussed above convey the idea that for each output characteristic (i.e., journey length, cost, duration, and carbon emissions) different vehicles perform differently depending on the network knowledge provided/accepted by drivers via telematics. What if a particular urban freight context does not conform to the archetypes presented? In this case it is possible to increase the generalizability of the results with recourse back to the connectivity coefficients discussed earlier. These can be applied to any transport network, of any size or type, in order to reveal its underlying level of connectivity. A fundamental relationship emerges: as the telematics penetration rate increases from 0% to 100% in a road network with Beta (β) ≥ 1.9 , journey costs, journey duration, and carbon output tend to improve (or at least do not worsen). In networks with $\beta < 1.9$, there is no added benefit of providing anything more than 50% telematics penetration. Figure 18.8

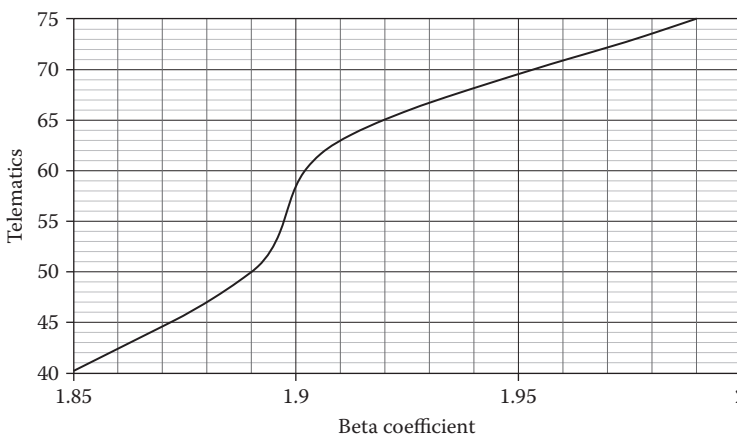


FIGURE 18.8

Relationship between the Beta coefficient (β) and the level of telematics required to optimize journey length, duration, cost, and carbon outputs.

illustrates the relationship between β and telematics within the range of data observed. [Figure 18.8](#) represents a simple diagnostic for answering the question: “what are the benefits of increasing drivers’ knowledge of the wider network conditions, via telematics, in a particular operating environment?”

18.4 Conclusions

Contrary to general belief, this study shows that there is a point at which more telematics does not lead to more efficient urban logistics. Indeed, in many cases the same outcomes can be achieved with 0% telematics as it can with 100%. Simply introducing an abundance of telematics into an urban freight situation, with planners and company policy enforcing 100% compliance with route guidance, however feasible that may be, will not result in the outcomes expected. This study shows that the topography of an urban street layout is an important contingency factor in how and when to deploy this technology. Both street pattern and route guidance interact to create congestion in the network, define who gets caught in it, and to what collective effects on time, cost, distance, and carbon emissions.

This is an exploratory study but a number of potentially important implications arise from it. The first relates to previous research that shows between 30% and 50% of drivers do not comply with telematics-based route guidance no matter how much of it is provided. As the results show, middle values like these represent an optimum on many outcome variables and street network types. This raises an interesting point. Does this established 30%–50% driver acceptance of route guidance arise through repeated experience of traffic conditions on a network, the implication being that driver behaviors (and the network itself) are self-organizing? If this is the case, then is the imposition of telematics based on a false premise? Does “everyone” in the network need to know “everything?” The results of this study would seem to suggest that, for some network types, they do not. If this is the case then the same outcomes could be achieved for considerably reduced cost.

The second implication relates to the different telematics strategies that urban logistics providers could adopt, and when? Is a costly strategy of providing complete knowledge of the network to drivers, and enforcing compliance with route guidance, optimum in all situations? No. Likewise, is a *laissez fair* approach to planning and route guidance, based purely on ad hoc local knowledge brought to situations by individual drivers, optimum? Again, no. Optimization is contingent upon the topology of the network being traveled upon. There are clearly some situations where it would benefit outcome variables such as carbon emissions to impose compliance with route guidance, and other situations where it would not be appropriate. The results of this study are helpful in understanding what these relationships might be and what an “adaptive telematics” strategy might look like. It would be a form of route guidance that would be cognitively compatible with drivers. One in which the timing and sequence of route guidance information would be oriented around different outcome variables at different times, but in all cases offering tangible journey based “rewards” for the driver. These rewards would encourage telematics to be used in ways that exceed the current 30%–50% acceptance rate where it is beneficial to do so, and as such, to accumulate some significant marginal gains.

Acknowledgment

This research benefitted from a collaboration between Heriot-Watt University and SIAS Transport Planners, 37 Manor Place, Edinburgh, [UK]EH3 7EB, the developers of the traffic microsimulation software S-Paramics.

References

- Asvin, G. 2008. *Fleet Telematics: Real-Time Management and Planning of Commercial Vehicle Operations*. Boston, Massachusetts: Springer.
- Bonsall, P. 1992. The influence of route guidance on route choice in urban networks. *Transportation*, 19, 1–23.
- Bonsall, P. W. and Palmer, I. 1999. Behavioural response to roadside variable message signs: Factors affecting compliance. In: Emmerick, R and Nijkamp, P. (eds). *Behavioural and Network Impacts of Driver Information Systems*. Farnham: Ashgate.
- Bowen, J. T. 2012. A spatial analysis of FedEx and UPS: Hubs, spokes, and network structure. *Journal of Transport Geography*, 24, 419–431.
- Brindle, R. E. 1996. *Urban Road Classification and Local Street Function*. South Vermont, Australia: Australian Road Research Board.
- Cherrett, T., Allen, J., McLeod, F., Maynard, S., Hickford, A., and Browne, M. 2012. Understanding urban freight activity—Key issues for freight planning. *Journal of Transport Geography*, 24, 22–32.
- Chorus et al. 2006. Use and effects of advanced traveller information services (ATIS): A review of the literature. *Transport Reviews*, 26(2), 127–149.
- Dutton, G. 2011. Fleet management's magic box. *World Trade*, 24(2), 38–44.
- Frey, H. 1999. *Designing the City: Towards a More Sustainable Urban Form*. London: Routledge.
- Giannopoulos, G. A. 1996. Implications of European transport telematics on advanced logistics and distribution. *Transport Logistics*, 1(1), 31–49.
- Harary, F. 1994. *Graph Theory*. Reading, Massachusetts: Addison-Wesley.
- Hesse, M. and Rodrigue, J. P. 2004. The transport geography of logistics and freight distribution. *Journal of Transport Geography*, 12(3), 171–184.
- Karl, C. A. and Bechervaise, N. E. 2003. The learning driver: Issues for provision of traveller information services. In *10th World Congress and Exhibition on Intelligent Transport Systems and Services*, Madrid.
- Leavitt, H. J. 1951. Some effects of certain communication patterns on group performance. *Journal of Abnormal and Social Psychology*, 46, 38–50.
- Lowe, J. C. 1975. *The Geography of Movement*. Boston: Houghton Mifflin.
- Lynch, K. 1981. *A Theory of Good City Form*. Cambridge: MIT Press.
- Lyons, G., Avineri, E., and Farag, S. 2008. Assessing the demand for travel information: Do we really want to know? In *Proceedings of the European Transport Conference*, Noordwijkerhout, Netherlands, October. <http://abstracts.aetransport.org/paper/index/id/2964/confid/14>
- Marshall, S. 2005. *Streets and Patterns*. Oxon: Spon Press.
- Moholy-Nagy, S. 1969. *Matrix of Man: Illustrated History of Urban Environment*. New York: Praeger.
- Monge, P. R. and Contractor, N. S. 2003. *Theories of Communication Networks*. New York: Oxford University Press.
- Nijkamp, P., Pepping, G., and Banister, D. 1997. *Telematics and Transport Behaviour*. Berlin: Springer-Verlag.

- O'Kelly, M. E. 1998. A geographer's analysis of hub-and-spoke networks. *Journal of Transport Geography*, 6(3), 171–186.
- Pugh, D. S., Hickson, D. J., Hinings, C. R., and Turner, C. 1968. Dimensions of organisation structure. *Administrative Science Quarterly*, 13(1), 65–105.
- Reggiani, A., Lampugnani, G., Nijkamp, P., and Pepping, G. 1995. Towards a typology of European inter-urban transport corridors for advanced transport telematics applications. *Journal of Transport Geography*, 3(1), 53–67.
- Satoh, S. 1998. Urban design and change in Japanese castle towns. *Built Environment*, 24(4), 217–234.
- Scottish Government. 2012. *Road-Traffic Count*. Accessed 2012. <http://www.transport.gov.scot/road/traffic-count>
- Thomson, J. M. 1977. *Great Cities and Their Traffic*. London: Victor Gollancz Ltd.
- Unwin, R. 1920. *Town Planning in Practice: An Introduction to the Art of Designing Cities and Suburbs*. London: Adelphi Terrace.
- Watts, D. J. and Strogatz, S. H. 1998. Collective dynamics of “small-world” networks. *Nature*, 393(4), 440–442.