PRIMARY AND SECONDARY EFFECTS OF TELEWORKING POLICIES ON HOUSEHOLD ENERGY CONSUMPTION

Dujuan YANG, Urban Planning Group Eindhoven University of Technology, the Netherlands, d.yang@tue.nl

Theo ARENTZE, Urban Planning Group Eindhoven University of Technology, the Netherlands, T.A.Arentze@tue.nl

Harry TIMMERMANS, Urban Planning Group Eindhoven University of Technology, the Netherlands, h.j.p.timmermans@tue.nl

ABSTRACT

In the transportation literature, the effects of teleworking have been studied primarily in terms of their effect on changing activity-travel patterns. Teleworking has been positioned as a policy to reduce the number of miles travelled and the number of trips. Potentially therefore, teleworking may contribute to a reduction of congestion and emissions. More recently, the discussion on sustainable development in the transportation research literature has been widened to include energy consumption. Increasing energy prices and expected energy shortages are believed to have an impact on travel behaviour. Consequently, the evaluation of teleworking policies should include this wider policy frame of reference. By estimating energy consumption as a function of characteristics of the activity-location, energy consumption related to daily activity-travel patterns can be simulated, at least to some level of detail. The primary and secondly effects of various policy scenarios, including teleworking, can then be evaluated by using an activity-based model to predict household response to the policy of interest. The paper reports the results of a study that was undertaken to examine the feasibility of this approach.

Keywords: energy consumption, activity-travel patterns

INTRODUCTION

Due to demographic factors such as population growth, increasing incomes, increasing energy prices and expected energy shortages, vehicle miles travelled are rising. Teleworking as an alternative way of organizing work is welcomed by governments and metropolitan planning organizations. There is more than one definition of teleworking (Handy 1995). In this study, we use the narrow definition of teleworking: working at home using communication and information technology instead of working at a company office. It has been often positioned as a viable strategy for reducing vehicle miles travelled, congestion on the road and improving air quality. In Europe, there are 1.2 million to 4.6 million telecommuters (Korte 1996; Bonn 2000). In United States, many metropolitan areas forecasted an increase in telecommuters as high as 8% in the near future (National Environmental Policy Institute 2000). The increase in the number of teleworkers' over the years reflects the results of implemented teleworking policies, made possible by the growth information technology services and telecommunications.

Current teleworking research has focused mainly on the impact on activity-travel patterns and a little on corresponding emission reduction (Shafizadeh 2000). Theories and models of employer and employee behaviour have been devised widely (e.g., Mokhtarian 1996). Yen and Mahmassani (1997) used the stated-preference approach to model under which conditions employees likely telecommute. In contrast, Ruppel and Harrington (1995) applied innovation theory to identify variables which affect organizations to adopt a teleworking program. Also, Monte Carlo simulation methods have been used to help illustrating the conditions under which the business case for telecommuting is supported or weakened (Shafizadeh 2007). As for environmental impacts, a number of studies have been conducted with respect to energy consumption issues (Walls 2004; Choo 2005). Koenig et al. (1996) estimated the impact of home-based telecommuting on travel behaviour and personal vehicle emissions using EMFAC7 and found a 77% decrease in VMT, 27% reduction in the number of personal vehicle trips, and 39%(4%) decrease in the number of cold(hot) engine starts. A systems model of telework and non-telework scenarios has been applied by Kitou and Horvath (2003) to quantify emissions in the United States. Although differences about the impact of teleworking on emissions reduction can be observed, the majority of authors do insist on encouraging telecommuting (Walls 2007).

The motivation underlying this study is that the dominant emphasis on emission and congestion reduction may only tell part of the story. The impact of teleworking policies should also be examined from the perspective of energy. Does teleworking lead to reduced energy consumption, relative to employees working in offices? The answer to this question requires a method to systematically link energy consumption to activities conducted at particular locations and energy consumption due to travel. The results of such calculations can then be viewed as another performance indicator. Ultimately, these calculations should be linked to an activity-based model of transport demand. This model can then be used to predict or simulate the primary and secondary effects of different policies, including teleworking, on changes in activity-travel patterns. The changes can then be assessed in terms of their effect on energy consumption.

This paper therefore presents an energy consumption model. The ultimate goal is to integrate this model with one of our activity-based models (e.g. Albatross). One of the critical conditions influencing the success of this approach is whether sufficient statistics are readily available. Therefore, we decided to first explore this issue for the Dutch context using data from a nationwide travel survey as opposed to an activity-based model. The calculation of energy consumption is illustrated using teleworking as an example.

The paper is organized as follows. First, we outline a comprehensive energy consumption model of teleworking based on household travel behaviour. Then, we analyse energy consumption for a non-teleworking and a teleworking scenario separately using the MON (Dutch travel Survey) data as input. Next, the results of the analyses are presented. The paper is completed by summarizing the major conclusions.

APPROACH AND MODEL

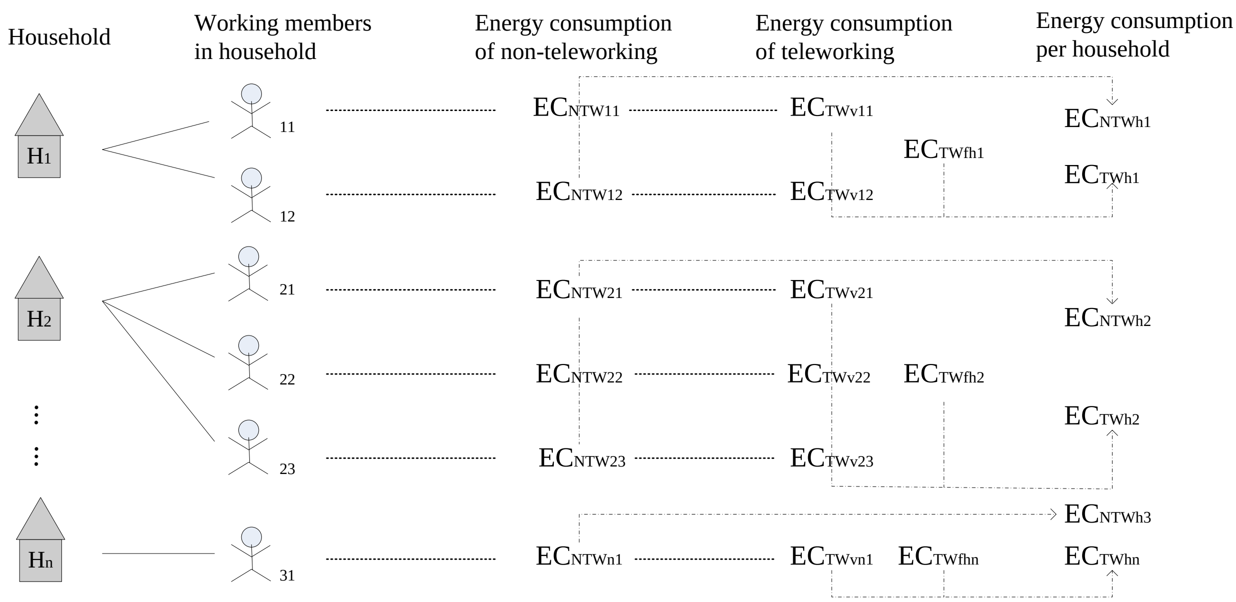

Figure 1 – Model of teleworking/ non-teleworking

The energy consumption model for teleworking which is implemented using Python programming includes not only the transportation part but also other components of the affected systems: heating, cooling, lighting, electronic and electrical equipment used in the office and at home. Activity-travel diary data are used to trace how much time people spend at a particular location, the activity involved and the amount of energy consumed. As a teleworking policy may not have the same effect on all types of households, and the working members in the household have their own activity patterns which could differently affect energy consumption, the approach adopted in this study aims at revealing the impacts of teleworking for different kinds of households.

Because activity-travel patterns and energy consumption are influenced by household decisions (Pratt 1999), we analyze energy consumption from the household rather than the person perspective. A comprehensive energy consumption model of non-teleworking (EC_{NTWi}) and teleworking (EC_{TWi}) based on households should however be partly disaggregated into person-level consumption patterns due to their different activity-travel patterns. In the model, household energy consumption for the NTW case is defined as:

$$EC_{NTWi} = \sum_{n=1}^{N} EC_{NTWin} \tag{1}$$

Where *i* is an index of household and *n* is the total number of working members in household *i*. For the TW case this energy consumption is defined as:

$$EC_{TWi} = EC_{TWfi} + \sum_{n=1}^{N} EC_{TWvin} \tag{2}$$

Where EC_{TWfi} is the basic energy consumption at home no matter how many people stay at home during the same time, f standing for the fix part of the energy consumption. And EC_{TWvi} is the consumption caused by electronic equipment used for teleworking: desktop PC's, fax machine, laser printer and copier, v standing for variable part. The difference in energy consumption between non-teleworking (EC_{NTWi}) and teleworking (EC_{TWi}) is given by:

$$EC_{di} = EC_{NTWi} - EC_{TWi} \tag{3}$$

The system's framework for analyzing effects of teleworking is presented in Figure 1. The unit of the analysis chosen for the model is a one-day diary, acknowledging that every person's activity and travel pattern covers a full day. We assume in the present application that individuals when they decide to telework will not increase or reduce the number of non-work trips on the considered day. Of course, this assumption may not be valid, but a model would be required to predict any change in the number of such trips due to teleworking. Using activity-travel diary data, we first calculate the energy consumption of the daily working trips and working in the office for each worker in the dataset, and then compare energy consumption under an assumption of teleworking, where all working members in the household would work from home on the same day during their working hours. Figure 2 explains the structure of the system. There are three parts in this model.

The first part represents the transportation energy consumption component. Teleworking has been considered widely as an effective way to reduce vehicle miles traveled. The actual energy saving is determined by the mode of transportation and the number of miles that are ultimately not travelled because of teleworking. The following modes of transportation are included in the model: foot, bicycle, bicycle as passenger, buggy, skates, transport for disabled, car driver, taxi, car passenger, bus, coach, tram/metro, train, moped, motorcycle, scooter, tractor, van, truck, boat (scheduled ferry) and aircraft. This is the list of modes included in the MON database – the travel survey used in this study. If the energy consumption calculations are linked to an activity-based model, some of these categories will need to be merged such that the classification of modes for calculating energy consumption is consistent with the categorization of transportation modes used in the activity-based model. The distances travelled include the kilometres travelled in the Netherlands and the kilometres travelled abroad. The data used does not provide direct information about sharing a car among household members. We assume that when one member is a car driver and the other a car passenger and the trips have the same start time, they share a car. Thus, the energy consumption of the trip in this household should be calculated only for the car driver. There is a small probability that the roles of driver and passenger are changed at a drop-off point, and to the extent this happens, the calculation will be biased. To calculate energy consumption of vehicles, we need to know the energy consumption for different transportation modes per kilometre.

The second part of the model relates to effects of working in the office. Energy consumption at the company office has not yet been comprehensively assessed and quantified in the context of teleworking. Here we focus on the following variables influencing energy consumption in the office: Area per person, space, cooling, hot water, wetting, miscellaneous, catering, ICT center, ICT decentralized, pumps, product, preparation, product cooling, transport ventilation, lighting within, lights out, and emergency lighting. We assume that energy consumption in offices could be differentiated by space and time. In the present study, we consider the average work space for a person in the Netherlands and their activity duration.

The third part of the model considers the effects of working at home. The model component can be divided into two parts. One part is the basic energy consumption at home (EC_{TWfhi}) including lighting, heating and cooling. The other part of consumption is caused by electronic equipment used for teleworking (EC_{TWvhi}): desktop PC's, fax machine, laser printer and copier. How to calculate the basic energy consumption offers a challenge: the amount of energy consumption of two persons staying at home at the same time is not twice the amount of one person staying at home. As reflected in Equation 2, we solved this problem by calculating the basic energy consumption at the household level instead of for every person separately, eliminating any double-counting. We assumed in the scenarios that the hours of teleworking are the same as those observed for working in the office.

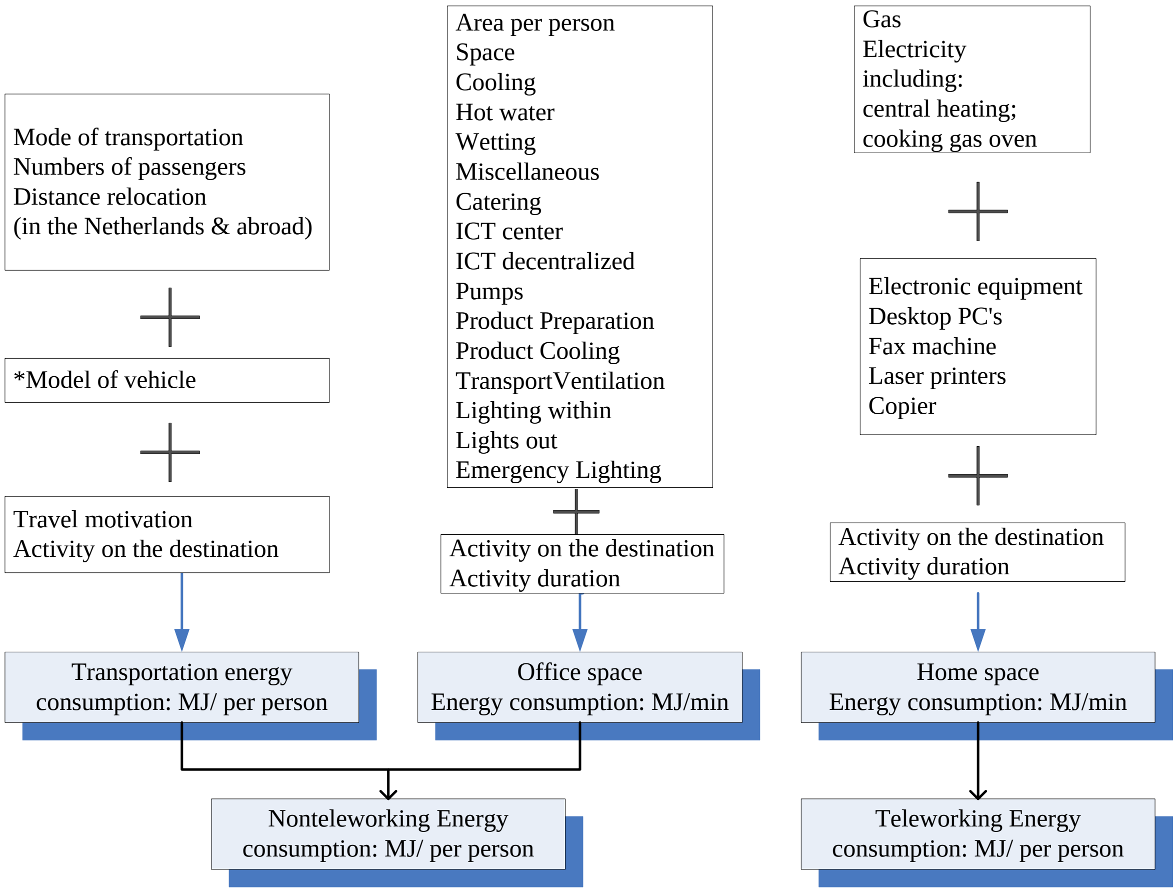

Figure 2 – The structure of the energy consumption model

The analysis according to this model includes the following steps. First, we select the working members of the household and record their daily trip information as the raw data. Trips of these working members that are not related to their work are eliminated, as they are irrelevant for the comparison. Trip purpose and activity at the destination are the data used here to identify work trips and activities. In the next step, we calculate the energy consumption including transportation part and working in the office part. Third, we calculate an estimate of the energy they would have consumed in case of tele-working (keeping everything else equal) by removing their working trips and changing their working place form office to home. In this analysis, energy consumption estimates are based on energy consumption data.

DATA

The basic data used for deriving the activity-travel pattern originates from the Dutch National Travel Survey (MON = Mobiliteit Onderzoek Netherlands) which was collected in 2004 and covered all provinces in the Netherlands. The data are collected for all household members and the diary day. The database also includes general household and person data such as, number of household members, number of younger family members, household composition, possession of vehicles in the household, gender, age, , education, income, etc. Respondents provided information about all trips made on the designated day as well as the activities conducted at trip destinations. Trip information includes start time, end time, trip purpose, origin, destination, activity type at the destination, activity duration and transport mode, etc. Overall, this is a comprehensive data source for analyzing activity-travel behaviour of Dutch residents. It consists of 28,600 valid household data for further analysis. In this study, we focus on the working members in the household and their effective work trips. Consequently, 12,696 households were used for energy consumption analysis.

Table I – Energy consumption of vehicle

vehicle	energy consumption (MJ/km)
car	2.6
Bus	13.97
trams	0.53 per passenger kilometre
Metro	0.50 per passenger kilometre
Train (electric)	0.1 per passenger kilometre
Train (Diesel)	0.243 per passenger kilometre
moped	0.82
Motorcycle	
Motorcycle / Scooter	1.88

Table 2 – Energy consumption in office divided by function

function	Energy consumption per year (MJ/m^2)
Space	500
Cooling	70
Hot water	6
Wetting	2
Miscellaneous	25
Catering	50
ICT centre	150
ICT decentralized	90
Pumps	15
Product Preparation	0
Product Cooling	0
Transport	15
Ventilation	40
Lighting within	260
Lights out	10
Emergency Lighting	5
Total	1,238

Table 3 – Basic energy consumption at home

	2004	2005	2006	2007	2008	2009
central heating [m3]	-	1,237	1,202	1,109	1,192	-
Cooking gas oven + [m3]	-	63	67	64	63	-
hot water [m3]	-	383	383	379	366	-
Electricity fixed costs [euro]	67	79	82	82	87	199
variable electricity costs [euro / kwh]	0.0812	0.088	0.0973	0.115	0.1105	0.0903
Electricity EPS / EB per kWh [Euro / kwh]	0.0654	0.0699	0.0705	0.0716	0.0727	0.1085
electricity tax [euro]	181	194	197	199	199	319
Electricity MEP [euro]	39	52	52	-	-	-
electricity invoice amount inc VAT [Euro]	416	473	507	540	540	598
Electricity VAT [Euro]	79	90	96	103	103	114
electricity invoice amount incl VAT [Euro]	495	563	604	642	643	712
electricity per kWh incl VAT [Euro / kwh]	0.1479	0.1658	0.1775	0.1824	0.1807	0.2
per household electricity consumption [kWh]	3,346	3,397	3,402	3,521	3,558	3,430
fixed gas costs [euro]	84	117	121	120	122	151
variable gas costs [Euro/m3]	0.2519	0.2833	0.3302	0.3729	0.3919	0.3558
EPS gas / EB per m3 [Euro/m3]	0.1429	0.1494	0.1507	0.1531	0.1554	0.158
gas invoice amount inc VAT [Euro]	770	837	911	940	1,170	1,285
Gas Tax [euro]	146	159	173	179	222	244
gas invoice amount incl VAT [Euro]	916	996	1,084	1,119	1,392	1,529
gas per m3 incl VAT [Euro/m3]	0.5276	0.5985	0.6598	0.7174	0.7271	0.7987
gas consumption per household [m3]	1,736	1,664	1,643	1,560	1,625	1,608
gas + electricity invoice amount inc VAT [Euro]	1,186	1,310	1,418	1,480	1,710	1,883
gas + electricity VAT [Euro]	218	239	260	281	325	358
gas + electricity invoice amount incl VAT [Euro]	1,403	1,549	1,678	1,761	2,035	2,240
gas + electricity index (2000 = 100) [index]	127	141	152	160	185	203

We obtained energy consumption data of vehicles in the Netherlands form the Dutch Ministries of Transport (Netherlands Institute for Transport Policy Analysis, KiM) and the Environment, and CE Delft (Boer 2008). The data for vehicle energy consumption per kilometer cover both real-world average performance and specific technologies like Euro emission classes, and fuels. Table 1 represents the energy consumption of variable kinds vehicle included in the report of CE Delft.

The energy consumption data at home and in the office was derived from the website of the NL Agency which is established under the responsibility of the Ministry of Housing, Spatial Planning and the Environment in the Netherlands (NL 2008) shown in Tables 2 and 3. The energy consumption data for houses were collected for a fixed group of respondents; a representative panel of over 3,500 households. Working with this annual panel, the degree of insulation of the house, hot water and heating are determined much more accurately than what is obtained in an ad hoc study with varying samples. The data for office buildings is based on a sample of 185 offices in the Netherlands. The data covers 15 different functions in the offices and average gas consumption per m^2 and electricity consumption per m^2 (Hoevenagel 2009). Table 4 shows the data of average energy consumption of office equipments at home which were retrieved from the website of home energy efficiency survey.

Table 4 – Average energy consumption of office equipment at home

Equipment	Conventional Products(kWh)	1kwh=3.6MJ	1year	MJ/min
Desktop PC's	500	1800	525600	0.0034
Fax Machines	300	1080	525600	0.0021
Laser Printers	750	2700	525600	0.0051
Copier (Medium)	1200	4320	525600	0.0082
Copier (Large)	2800	10080	525600	0.0192

RESULTS

Comparing energy consumption of teleworking and non-teleworking

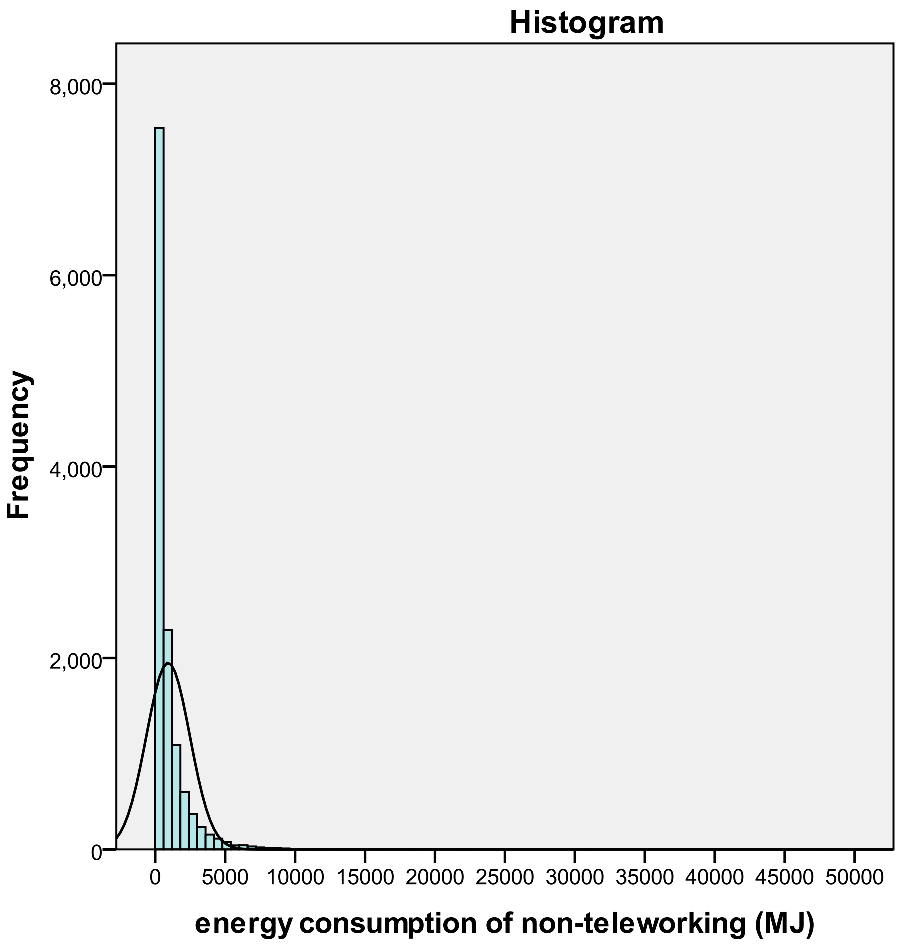

Figure 3 – Distribution of non-teleworking energy consumption

Figure 3 shows the distribution of energy consumption in the case of non-teleworking. It covers the spectrum from 0 MJ to over 7000MJ. It is clear from this figure that the mean energy consumption of non-teleworking in households is 936.85 MJ, while around 86.6% households spend less than 1800 MJ on their non-teleworking day. Less than 1800 households consume over 1800 MJ. In comparison, energy consumption in case of teleworking, given the assumptions made, is much less than energy consumption for the case of non-teleworking. As can be seen from Figure 4, no more than 200MJ is used by households on their teleworking day. The energy consumption of 56.3% of the households is between 80MJ and 120MJ, and over 15.8% households spend less than 50MJ.

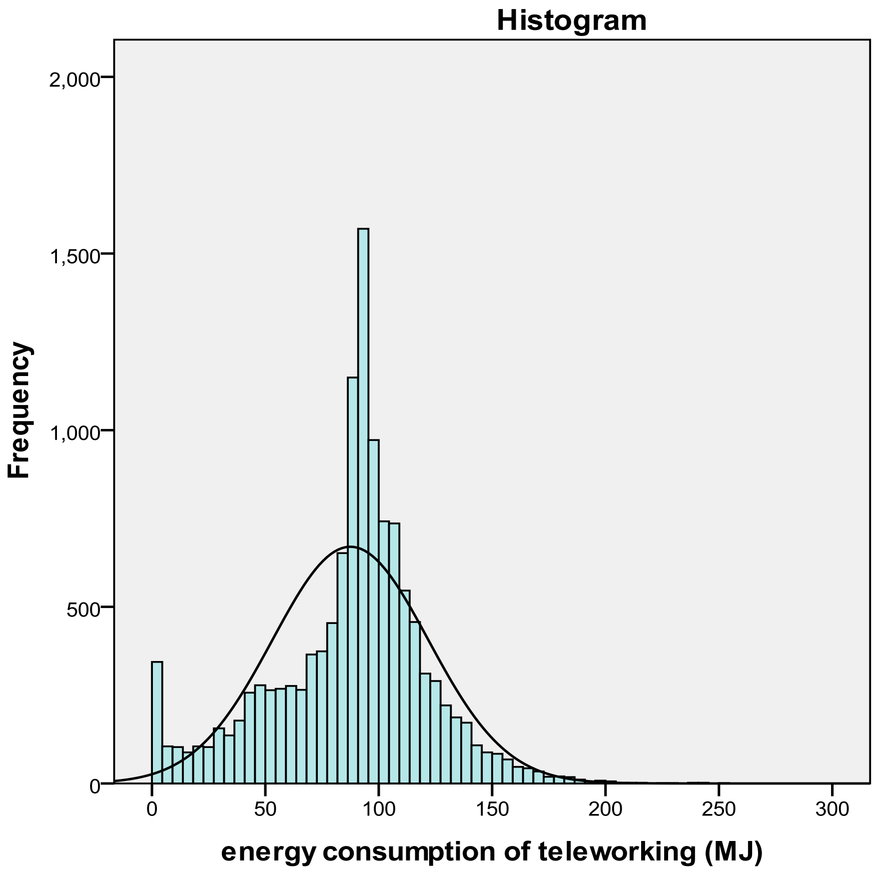

Figure 4 – Distribution of teleworking energy consumption

Figure 5 shows the distribution the difference in energy consumption between the non-teleworking and the tele-working scenarios, EC_d. It indicates that in most households, teleworking coincides with a reduction of the energy consumption. However, in 9.6% of the households, energy consumption increases due to teleworking. This could be partly explained by the following two reasons: first, reducing trips for working does not save much energy for these households because their vehicles for travel cost less energy or no energy at all such as bike, on foot, etc.. Another reason is that the distance travelled for work is short. Their working time may also be longer. Compared to the energy consumption of

0.053MJ/min in the office, it will cost more energy if people working at home which involves an energy consumption of 0.151MJ/min.

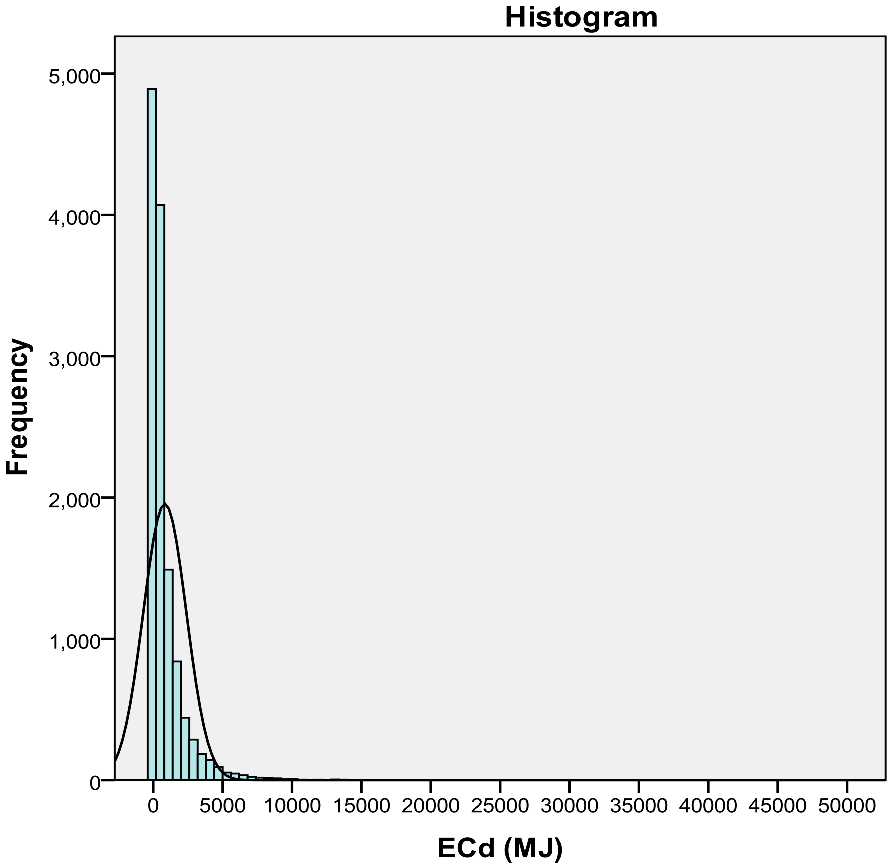

Figure 5 –Distribution of energy consumption difference between non-teleworking with teleworking

Table 5 – Classification of household variables

No.	Variable	Category	Description
1	number of people in household (N_1)	1	Household composition
2	number of family members younger than 6 years old (N_2)		
3	number of family members from 6 to 11 years old(N_3)		
4	number of family members from 12 to 17 years old(N_4)		
5	number of family members older than 17 years old(N_5)		
6	Number of cars in household(N_6)	2	Available vehicles
7	Number of bikes in household(N_7)		
8	number of motors in household(N_8)		
9	number of mopeds in household(N_9)		
10	Weekday (N_{12})	3	Temporal information
11	Month (N_{14})		

In addition to these averages, we analyzed the relationship between household variables and EC_d. There are 11 household variables in the MON data that may influence energy consumption. As shown in Table 1, we divided these into 3 categories: variables related to household composition, variables related to the number of and kind of vehicles available in the household and temporal information related to the observed diary day. The households were split into two groups, depending on whether or not the variable EC_d is positive. The "P" or positive group is the group of households for which this variable is positive difference, whereas for the "N" group the difference in energy consumption between the non-teleworking and tele-working scenarios is negative.

We first analyzed the effect of day of the week and month of the year on energy consumption. However, as suggested by Table 6, correlations are weak.

Table 6 –Effects of day of the week and month of the year on average energy consumption

Percent / weekday/month	weekday		month	
	P	N	P	N
Monday/Jan.	2.2	2.1	6.5	6.6
Tuesday/ Feb.	19.0	18.4	6.2	5.5
Wednesday/ Mar.	19.6	17.7	7.3	7.8
Tuesday/ Apr.	19.1	17.4	6.1	5.5
Friday/ May	19.4	18.0	6.2	5.7
Saturday/ June	16.7	18.8	7.0	5.9
Sunday/ July	4.1	7.7	6.3	7.1
Aug.			6.9	6.4
Sept.			12.6	14.8
Oct.			13.0	12.5
Nov.			13.9	13.5
Dec.			7.9	8.7

Then, T-test was used to show whether there is significant difference between N group and P group on these variables showed in table 5 except the temporal information. According to Table 7, the output gives the inferential statistics. The columns labelled "Levene's Test" tell us whether an assumption of the t-test has been met. The α level for this test is 0.05, if the significance (p value) of Levene's test is less than or equal to 0.05, we reject the null hypothesis that the variances of the two groups are equal. In this test, the α level of N1, N2, N3, N4, N5, N6, N7 are less than our α level, so we will assume that the variances are unequal. Then looking at all variables output of sig., if p is not less than or equal to 0.05, we fail to reject the hypotheses. Here, N_1 (.000), N_2 (.019), N_5 (.000), N_6 (.000), N_7 (.000), N_8 (.000), which implying that there are difference between these two groups in these six variables.

Looking back to the data we have, we could get that the proportion of these two groups does not differ that much when the age of the people in the family between 6 to 17 years old. Households that evidence reduced energy consumption tend to consist of households with more more than 18 years old people and less than 6 years old children, besides less family members. It suggests that more people working at home at the same time tend to reduce energy consumption. Form the view of available vehicles in the household, the percentage of households owning one and more cars and motors and less bikes in the "P" group is higher than the corresponding percentage in the "N" group which is consistent with the fact that households having more cars, motors use more energy for the work trip.

Table 7 – The result of T-test

Variable		Levene's Test		t-test for Equality of Means		
		F	Sig.	t	Sig. (2-tailed)	Mean Difference
N_1	Equal variances assumed	4.889	0.027	7.434	0	0.293
	Equal variances not assumed			7.242	0	0.293
N_2	Equal variances assumed	17.208	0	2.222	0.026	0.04
	Equal variances not assumed			2.353	0.019	0.04
N_3	Equal variances assumed	9.54	0.002	1.475	0.14	0.026
	Equal variances not assumed			1.581	0.114	0.026
N_4	Equal variances assumed	6.612	0.01	1.332	0.183	0.024
	Equal variances not assumed			1.373	0.17	0.024
N_5	Equal variances assumed	33.723	0	9.235	0	0.203
	Equal variances not assumed			9.009	0	0.203
N_6	Equal variances assumed	407.293	0	18.959	0	0.394
	Equal variances not assumed			20.762	0	0.394
N_7	Equal variances assumed	39.638	0	3.121	0.002	0.034
	Equal variances not assumed			3.912	0	0.034
N_8	Equal variances assumed	0.842	0.359	5.031	0	0.261
	Equal variances not assumed			5.135	0	0.261
N_9	Equal variances assumed	0.507	0.477	0.326	0.744	0.003
	Equal variances not assumed			0.351	0.726	0.003

Regression analysis

Table 8 – Regression model

	b	SE b	Beta
(Constant)	378.087	52.74	
Number of cars in the household (N_6)	181.470	26.71	.067***
number of family members older than 17 years old (N_5)	119.343	30.49	.046***
Number of mopeds in the household (N_8)	-136.031	54.33	-.022*
Number of bikes in the household (N_7)	54.503	14.33	.049***
number of people in the household (N_1)	-64.470	21.07	-.044**

Note. R^2=.007 for step 1; R^2=.008 for step 2; R^2=.009 for step 3, 4; R^2=.010 for step 5. *p<0.05, **p<0.01, ***p<0.001.

The previous analyses concerned the results for a basic classification into 2 groups: the N and the P group. Next, stepwise multiple regression analysis was used to analyze the effects of factors influencing energy consumption, that is, the relationships between difference in energy consumption and the variables N_1 to N_9. We used standard regression on the whole data, but the results showed that number of people in household is highly correlated with other variables. To eliminate the effect of multicollinearity and select the most significant variables, stepwise multiple regression was used to build the model.

The final regression equation equals

$$EC_d = 378.087 + 184.47 * N_6 + 119.343 * N_5 - 136.031 * N_8 + 54.503 * N_7 - 64.47 * N_1 \quad (4)$$

For the final model, the value of R^2 is 0.10, which means that the selected five independent variables account for only 10% of the variation in EC_d. Five significant variables finally entered the regression model shown in Table 5: number of children under 6 years old, number of cars, bikes and mopeds in the household and the total number of family members.

According to their coefficients, variables of N_1 and N_8 have negative effects on EC_d, which indicates that those households consisting of more persons or with more mopeds tend to experience an increase in energy consumption. Comparing these two variables, the number of mopeds in household has a stronger influence on energy use. Which means the household owning more mopeds would reduce less energy by teleworking. With increasing number of cars, bikes, and adults in the household, the household will save more energy if they work at home. The effect of the number of cars is the highest, which is consistent with the vehicle energy consumption data that cars use most energy per kilometre. It also indicates that reducing the use of cars by teleworking will save more energy than reducing the use of other kind of vehicles.

CONCLUSIONS AND DISCUSSION

Calculating energy consumption of activity-travel patterns would be a very useful extension of the set of performance indicators linked to activity-based models. It would allow assessing the impact of various policies not only in terms of the typical transportation performance measures and emissions, but also in terms of energy consumption. This extension is important in light of the expected shortage of energy, increased energy prices and the gradual shift to more integrated policy evaluations.

If an energy consumption model would be linked with an activity-based model of transport demand, the latter could be used to predict changes in activity-travel patterns that result from a policy and these changes can then be assessed in terms of their impact on energy consumption, in addition to other performance indicators. Crucial in the development of this idea is the availability of energy consumption data, not only for transport, but also for activity locations.

The primary purpose of the present study therefore has been to explore the potential of this avenue. The challenge was to search for readily available data and find common classifications to develop an operational method. The policy of teleworking was chosen as a case for illustration because this policy has usually been examined only in terms of miles traveled and emissions.

The results of this exercise demonstrate that at least for the Netherlands, a set of statistics can be found that allow one to derive energy consumption data from activity-travel patterns. It also shows that these data are crude averages. The question therefore becomes whether further disaggregation would be required to obtain more reliable assessments. For example, if energy consumption may vary by lifecycle, further disaggregation would be needed. Similarly, energy consumption differs by size and type of car, but this variation is currently not taken into account, also because most activity-based models do not differentiate between different kinds of cars. Another example relates to various characteristics of houses that influence energy consumption levels.

Whether such disaggregation is needed will depend on the specific policy. However, any disaggregation does not affect the principles behind the suggested approach in this study. It may imply that more detailed data collection is needed and that further statistical analysis should be done to analyze the relationship between energy consumption levels and influencing variables. In the Netherlands, some of this more detailed data has already been collected, but making these data available for research is still under debate for privacy reasons.

In terms of the illustration, keeping these considerations in mind, the results of the application suggest that teleworking, based on the assumptions made, will on average result in a reduction of energy consumption. This is mainly caused because, ceteris paribus, energy consumption for travel is higher than energy consumption for activities at home. Reduction however varies for example by household composition. If more people telework and use the house at the same time, reduction of energy consumption increases. Similarly, reduction in energy consumption will be higher in those cases, where vehicles using more energy will not be used due to teleworking.

There are still some improvements that need to be made in future research. First, as discussed, perhaps some statistics on energy consumption should be disaggregated. Most importantly, however, in this illustration we assumed that teleworking did not generate any additional non-work trips. This assumption should be replaced with an activity-based model of transport demand, which simulated the generation of any new non-work trips and the rescheduling of the activity-travel program in time and space.

ACKNOWLEDGEMENTS

The research leading to these results has received funding from the European Research Council under the European Community's Seventh Framework Programme (FP7/2007-2013) / ERC grant agreement n° 230517 (U4IA project).

The views and opinions expressed in this publication represent those of the authors only. The ERC and European Community are not liable for any use that may be made of the information in this publication.

REFERENCES

Bonn (2000). Telework Data Report (Population Survey). European Union.

Boer, E. D., F. Brouwer, H. van Essen (2008). Study on the Transport Emissions of All Modes (STREAM). Delft, the Netherlands.

Choo, S., M. Patricia L, S. Ilan (2005). Does telecommuting reduce vehicle-miles traveled? An aggregate time series analysis for the US. UC Davis: Retrieved from: http://www.escholarship.org/uc/item/74t9663f, Vol. 32(1), 37-64.

Handy, S.L., P. L. Mokhtarian (1995). Planning for telecommuting measurement and policy issues. Journal of the American Planning Association, Vol. 61(1), 99-111.

Hoevenagel, R., K. Brammer (2009). Energiebesparingsmonitor gebouwde omgeving: U-bouwpanel_Resultaten zesde meting 2008. Dutch, the Netherlands.

Kitou, E., A. Horvath (2003). Energy-related emissions from telework. Environmental Science & Technology, Vol. 37(16), 3467-3475.

Koenig, B., H. Dennis, M. Patricia (1996). The travel and emissions impacts of telecommuting for the state of California telecommuting pilot project. Institute of Transportation Studies, UC Davis, Vol. 4(1), 13-32.

Korte, W. B., N. Wynne, R. Wynne (1996). Telework Penetration Potential and Practice in Europe. Ios Pr Inc, Oxford.

Mokhtarian, P., and S. Ilan (1996). Modeling the choice of telecommuting 2: a case of the preferred impossible alternative. Environment and Planning A, Vol. 28(10), 1859-1876.

National Environmental Policy Institute (2000). The National Air Quality and Telecommuting Act (as Part of HR 2084): Final Report. Available: http://www.nepi.org/pubs/summary.pdf , Washington, DC.

NL (2008). Energy and energy conservation in Dutch houses. [Online], Available: http://www.senternovem.nl/kompas/energiecijfers/index.asp.

Pratt, J. H. (1999). Cost/Benefits of Teleworking to Manage Work/Life Responsibilities. Telework America National Telework Survey.

Ruppel, C.P., S. J. Harrington (1995). Telework: An innovation where nobody is getting on the bandwagon. Database Advances, Vol. 26(Nos. 2 & 3), 87-104.

Shafizadeh, K. R., M. Patricia L., N. Debbie A., S. Ilan (2000). The Cost and Benefits of Home-based Telecommuting. Research Reports. California.

Shafizadeh, K. R., N. Debbie A., M. Patricia L., S. Ilan (2007). Costs and benefits of home-based telecommuting: a Monte Carlo simulation model incorporating telecommuter, employer, and public sector perspectives. Journal of Infrastructure Systems. Vol. 13(1), 12-25.

Walls, M., P. Nelson, E. Safirova (2007). Telecommuting and environmental policy lessons from the ecommute program. Transportation Research Part D, 195-207.

Walls, M. and E. Safirova (2004). A review of the literature on telecommuting and its implications for vehicle travel and emissions. Resources for the future, 4-44.

Yen, J. and H. S. Mahmassani (1997). Telecommuting Adoption: Conceptual Framework and Model Estimation. Transportation Research Record, Vol. 1606, 95-102.