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Modelling electric vehicles and setting charging patterns endogenously in energy planning models

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In the UN Emissions Gap Report it is estimated that the action plan agreed in the Paris Climate Agreement is not sufficient to limit the global temperature increase to below 2°C, compared to the pre-industrial period. More stringent measures must be taken to reduce global warming. In order to evaluate the most suitable pathways to decarbonize economies, complex multisectoral models should be used. Electric vehicles have the potential to significantly reduce carbon emissions in the transport sector. However, high penetration of electric vehicles might affect the development of the power sector. Additional energy required to charge these vehicles increases overall electricity demand. Thus, even though a higher share of electric vehicles reduces emissions in the transport sector, overall emission reduction effect depends on the fuels used to generate this additional electricity for charging. In case of fossil fuels, overall emissions might even increase. On the other hand, it is possible to adjust charging patterns according to generation fluctuations in wind and solar power plants. Such energy balancing could allow higher penetration of intermittent renewables. Because of this interlinkage of power and transport sectors through electric vehicles it is beneficial to model both sectors simultaneously in energy planning models, especially when the purpose of the model is to evaluate possible emission reduction pathways.

In this paper, a methodology is proposed on how to model electric vehicles in energy planning models. This methodology enables flexible charging of electric vehicles, where charging patterns are set internally by the model. The methodology is based on the modelling of different driving patterns and evaluation of different vehicle states. Furthermore, it is explained how driving patterns and vehicle states can be derived from limited data by using pattern approximation with normal distributions.

Keywords: electric vehicle, charging, endogenously, energy planning, MESSAGE

INTRODUCTION

In the Paris Climate Agreement it was agreed to take action to limit the global temperature increase to below 2°C, compared to the pre-industrial period. Each country set its National Determined Contributions – an obligation to limit or reduce national greenhouse gas emissions. However, in the UN Emissions Gap Report 2018, which assesses the latest scientific studies on current and estimated future emissions, it is stated that global temperatures will increase by 2.9–3.4°C by the year 2100 even with Paris Climate Agreement pledges [1]. For this reason, more stringent measures are required to achieve set climate goals.

The transport sector is one of the biggest contributors to global greenhouse gas emissions. In 2016, 28% of EU-28 greenhouse gas was emitted in this sector [2]. Even though overall greenhouse gas emissions in the period from 1990 to 2016 were reduced, emissions from fuel combustion in the transport sector increased by 163 Mt CO_2 eq. From 2015 to 2016 it increased by 19 Mt CO_2 eq. [3] According to provisional data average CO_2 emissions from new cars sold in the EU increased in 2017 [4]. It is apparent that significant changes in the transport sector are necessary, which must be taken to limit the global temperature increase below 2°C.

Energy planning models like MESSAGE [5], TIMES [6], Balmorel [7], PRIMES [8] are widely used to conduct research on how the energy sector should be developed to meet environmental requirements. National energy strategies are often based on such research. However, many sectors are interconnected and multi-sectoral approach is beneficial or in some cases necessary even when the focus is on one sector. For example, when creating an energy planning model for the electricity sector of the country, in which a significant part of heat is produced in combined heat and power (CHP) plants, the heat sector should be also modelled, because electricity production in CHP plants depends on heat demand. Electric vehicles (EVs) similarly connect transport and power sectors. Research shows that inclusion of plug-in hybrid electric vehicles into a model affects the integration of wind and solar power plants [9]. Electricity demand for charging of these vehicles contributes to overall demand and affects the demand curve. This effect can be evaluated exogenously; however, if it is estimated that at some point in time a significant part of the fleet will be EVs, then charging patterns should be evaluated endogenously. It would give flexibility for the model to choose when to charge EVs. This approach is useful for decarbonization models, where high penetration of renewable sources is expected since this flexibility allows to partially absorb electricity production peaks from renewable sources.

Some researchers use models, where charging patterns for EVs are determined endogenously. However, in most cases charging availability is not taken into consideration. EV cannot be charged when it is in use; furthermore, when a vehicle is parked somewhere else than at home a chance that charging will be available depends on charging infrastructure, so this availability also has to be taken into consideration. Another issue is "car sharing", which has to be addressed. It is when a model can satisfy the travel demands of many people with the same vehicle. The aim of this paper is to propose a methodology on how to model EVs in energy planning models. This methodology was developed by modelling EV in MESSAGE software and addressing previously mentioned problems. A described modelling approach was tested on a simplified model of isolated Lithuanian energy and heat sectors. It should be noted that even though this methodology was developed and tested in MESSAGE software, it should still be applicable to models created using different energy planning models.

METHODOLOGY

Travel distributions and vehicle states

Electric vehicles are connected to the grid, i.e. charged when they are parked at home or at some charging station, which can be installed in the shopping mall, office and other parking lots. However, only some parking lots have installed charging stations, but probably all electric car owners can charge car at their home, so it is important to distinguish times when the car is parked at home (EV can be charged freely), somewhere else (availability of charging depends on charging infrastructure) and when it is being used (cannot be charged). For this reason, it is necessary to have hourly driving pattern data. Ideally, GPS-based travel pattern data from "Google"/"Waze" or "Apple" should be used. Since such data is unavailable, in this paper driving pattern data is derived from passenger flows in Vilnius public transport in 2016 [10]. It is assumed that the shape of an average hourly curve of person kilometres travelled (PKT) in lightweight vehicles should be similar to PKT in the public transport curve (1).

The dataset has data on time when each vehicle reached a stop, what is the distance travelled from last stop, vehicle filling (number of passengers). An algorithm was used to calculate PKT for each hour in 2016. Conditional summing was implemented to skip negative and unreasonably high values. There are some errors in this dataset, which might be caused by malfunctions in sensors.

$$PKT_h = \sum_{t=h}^{h+\frac{1}{24}} \sum_{v} \begin{cases} F_{t,v} \cdot D_{t,v}, & 0 < F_{t,v} < 300 \text{ and } 0 < D_{t,v} < 50 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$h = \left(42370\frac{0}{24}, 42370\frac{1}{24} \ldots 42735\frac{23}{24}\right), \quad (2)$$

$F_{t,v}$ – vehicle filling, $D_{t,v}$ – distance travelled, v – vehicle, t – stop date time.

It was noticed that driving patterns differ during Saturday, Sunday, Holiday (SSH) and workdays. During workdays there are two traffic peaks: morning peak at 7–8 A. M. and evening peak at 3–5 P. M. During SSH traffic gradually increases from 4 A. M. till 3 P. M., when it reaches its maximum value and decreases afterwards. In both cases, during the night time almost no one is traveling. However, it should be taken into consideration that only a few buses drive at these hours and people probably choose alternative means of transport like a taxi during these hours. It is assumed that for people who travel with cars the values during the night should be somewhat higher. This assumption is consistent with traffic patterns presented by various researchers [11–13]. These curves were adjusted and averaged, then values were recalculated in a way that it would represent what share of PKT is travelled in each hour (Fig. 1).

An assumption was made that the traffic profile curve consists of at least one departure and one arrival curves and these can be represented by normal distributions. To estimate departure and arrival curves from a traffic profile curve, an optimization problem was defined. The objective function of this optimization problem is a sum of square errors between pattern data and the estimated departure and arrival distribution combined data. This means, the smaller difference between the sum of estimated distributions and actual pattern, the lower value of an objective function. The evolutionary solver in MS Excel [14] was used to minimize the objective function by changing mean (μ_i) and dispersion

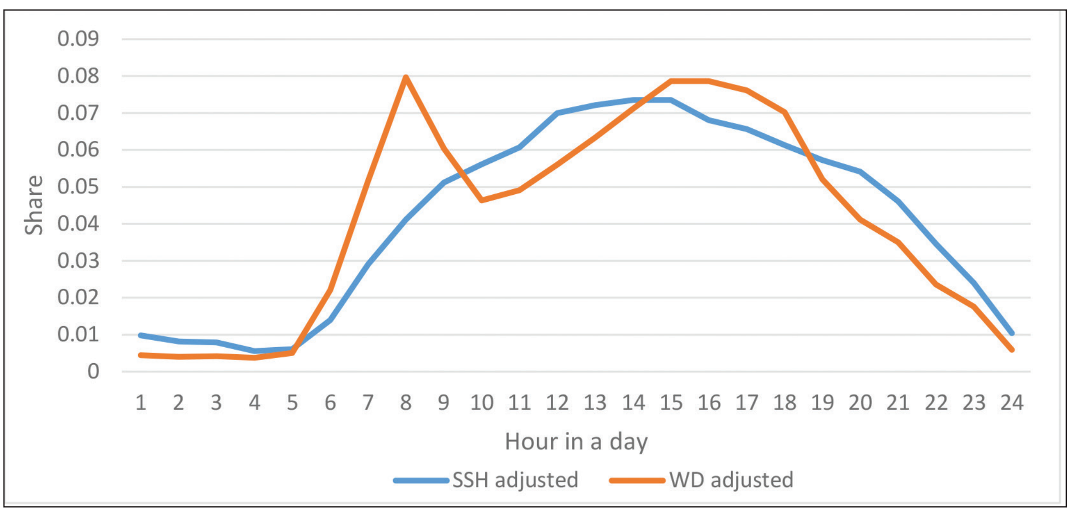

Fig. 1. Traffic profiles for SSH (Saturdays, Sundays, Holidays) and WD (workdays)

(σ_i^2) values of departure and arrival distributions ($P_i(h, \mu_i, \sigma_i^2)$). A number of distributions to be extracted from pattern data is defined with variable N. For a single departure and return N = 2. Index i is used to denote data of different distributions. F_h is a value of the original pattern for hour h. To avoid errors, additional constraints are placed. Mean values of distributions cannot be lower than 0 or higher than 24. Dispersion must be no less than 0. Equations of the defined optimization problem are given below:

$$\underset{\mu,\,\sigma^2,\alpha}{\text{minimize}} \sum_{h=1}^{24}\left(X_h - \sum_{i=1}^{N}\left(\alpha_i \cdot Q_i\left(h,\mu_i,\sigma_i^2\right)\right)\right)^2,$$

$$h = 1, 2, \ldots, 24,\ i = 1, 2, \ldots, N$$

$$\text{subject to } Q_i(h, \mu_i, \sigma_i^2) = P_i(h - 24, \mu_i, \sigma_i^2) +$$

$$+ P_i(h, \mu_i, \sigma_i^2) + P_i(h + 24, \mu_i, \sigma_i^2)$$

$$P_i\left(h,\mu_i,\sigma_i^2\right) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(h-\mu_i)^2}{(2\sigma_i^2)}}, \qquad (3)$$

$$0 \le \mu_i, \le 24,$$

$$\sigma_i^2 \ge 0,$$

$$\sum_{i=1}^{N} a_i = 1.$$

In the objective function three normal distribution values $P_i(h - 24, \mu_i, \sigma_i^2) + (P_i(h, \mu_i, \sigma_i^2) + (P_i(h + 24, \mu_i, \sigma_i^2)$ are summed to not lose values which are not within $h = (1 \ldots 24)$. The 25th hour is the same as the 1st hour. Values of different normal distributions are multiplied by the coefficient of magnitude α_i and then summed to combine them. The coefficient of magnitude shows what part of the combined curve will take a certain distribution. In this case, there are only 2 distributions ($N = 2$): one for departure and one for arrival. It was assumed that distance travelled is the same for traveling somewhere and returning; also all people that departed must return. Therefore, coefficients must be equal. Since the sum of these two coefficients must be 1, so the coefficient value for both distributions is equal to 0.5:

$$\alpha_1 = \alpha_2. \qquad (4)$$

Estimated departure and return distributions are shown in Fig. 2. Combination of departure and return distributions not perfectly but matches the SSH traffic pattern. It is possible to get better matching results by using a higher number of normal distributions. However, for the purpose of this paper, it was deemed unnecessary.

When departure and return distributions are known, it is possible to determine whether vehicles are on the road, parked somewhere or at home. However, this relies on two major assumptions. The first one is that departure and return distributions for vehicle count are the same as for PKT. The second one is that all travels take 1 hour.

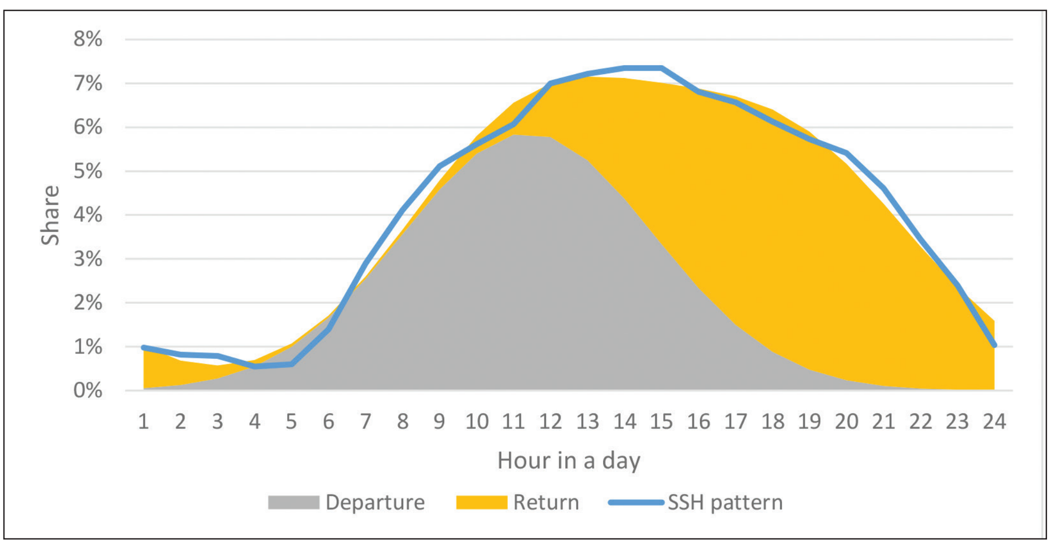

Fig. 2. SSH pattern with departure and return distributions

The share of vehicles at home ($H(h)$) can be calculated by subtracting the share of all departing vehicles ($\Sigma_{i \in D}$)($\beta_i \cdot P_i(h)$) from vehicles at home in a previous hour ($H(h-1)$) and adding vehicles that arrived home ($\Sigma_{i \in A}$)($\beta_i \cdot P_i(h-1)$)). β_1 is a coefficient which shows what part of all vehicles follow a corresponding travel distribution curve. When calculating a value for first hour, initial value $H(0)$ is needed. The share of vehicles at home at the 24th hour will be equal to H(0), so this value has to be chosen accordingly. In this example, it was assumed that 92% of vehicles should be at home at the 24th hour:

$$(h) = H(h-1) - \sum_{i \in D} \left(\beta_i \cdot P_i(h) \right) + \\ + \sum_{i \in A} \left(\beta_i \cdot P_i(h-1) \right),\ h = 1, 2, \ldots, 24 \tag{5}$$

$$P_{i \in A}(0) = P_{i \in A}(24). \tag{6}$$

In this example: H(0) = 0.92; N = 2; D = {1}; A = {2}; $\beta_i = 1$.

The share of vehicles on the road is equal to the sum of shares of arriving and departing vehicles:

$$R(h) = \sum_i \left(\beta_i \cdot P_i(h) \right). \tag{7}$$

Parked vehicles are calculated by subtracting shares of vehicles at home and on the road from 1:

$$K(h) = 1 - R(h) - H(h). \tag{8}$$

If some distribution index i does not belong to departure set D nor to arrival set A, then it is called that this distribution is of intermediary travel. It increases vehicles on the road and decreases parked cars, but it does not affect vehicle share at home.

When extracting departure and return distributions from the workday travel pattern it was found that a combination of 2 distributions does not represent travel pattern accurately enough. Therefore, 4 distributions were used (N = 4). Under the premise that some people have the same travel pattern during both workdays and SSH, 2 distributions were left the same as in SSH case, i.e. mean (μ_i) and dispersion values (σ_i^2) for i = 1; 2 distributions were fixed and set to ones calculated before. The shares of SSH distributions and new ones within WD curve are determined by the coefficients of magnitude (α_i). Coefficient values for departure and return are equal:

$$\alpha_1 = \alpha_2, \tag{9}$$

$$\alpha_3 = \alpha_4. \tag{10}$$

Combination of SSH distributions and 2 new ones gives acceptable results. Results are presented in Figs. 4, 5.

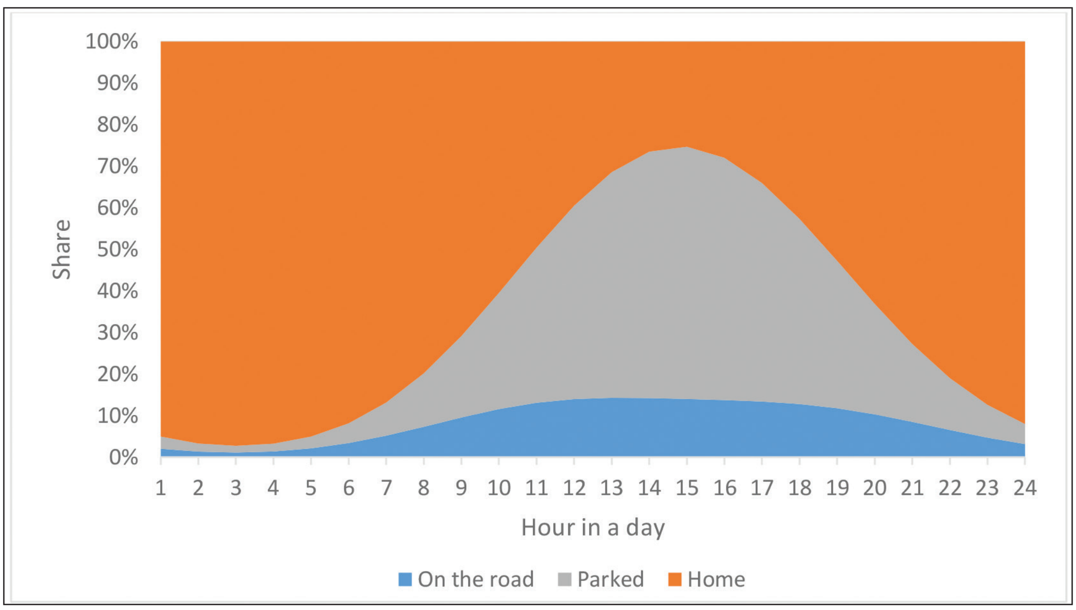

Fig. 3. Hourly vehicle shares by their state during SSH

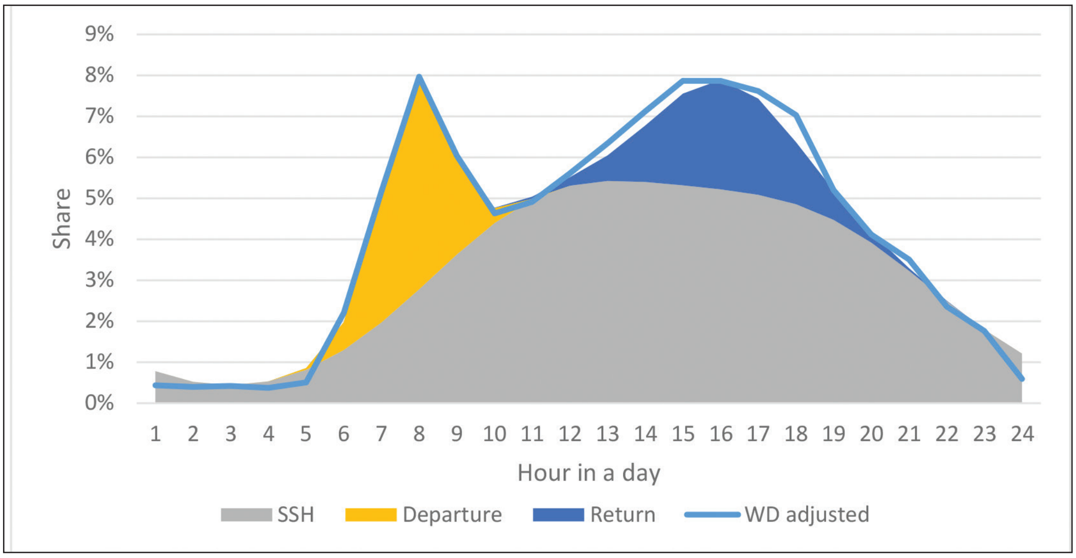

Fig. 4. WD pattern with departure, return and SSH distributions

From WD and SSH results we see that travel patterns can be separated into travel components. SSH pattern is made up only of one component and WD pattern from two. These components will be referred to as *traffic_other* and *traffic_work*. SSH pattern is the same as a *traffic_other* component. *traffic_work* and *traffic_other* will be modelled as separate travel demands, which will have to be satisfied by different technologies.

$$PKT_{other} = PKT \cdot (\alpha_1 = \alpha_2), \tag{11}$$

$$PKT_{work} = PKT \cdot (\alpha_3 = \alpha_4). \tag{12}$$

PKT values for components can be calculated by multiplying overall PKT by the sum of corresponding coefficients of magnitude. Overall PKT has to be acquired from statistical data.

Modelling electric vehicles in MESSAGE

Demand is the driving force of an optimization model. A model tries to satisfy the demands with the lowest costs, within given constraints. So, when modelling the transport sector there should be a demand for travel or, in other words, person kilometres travelled, which could be satisfied by different types of vehicles. As it was explained,

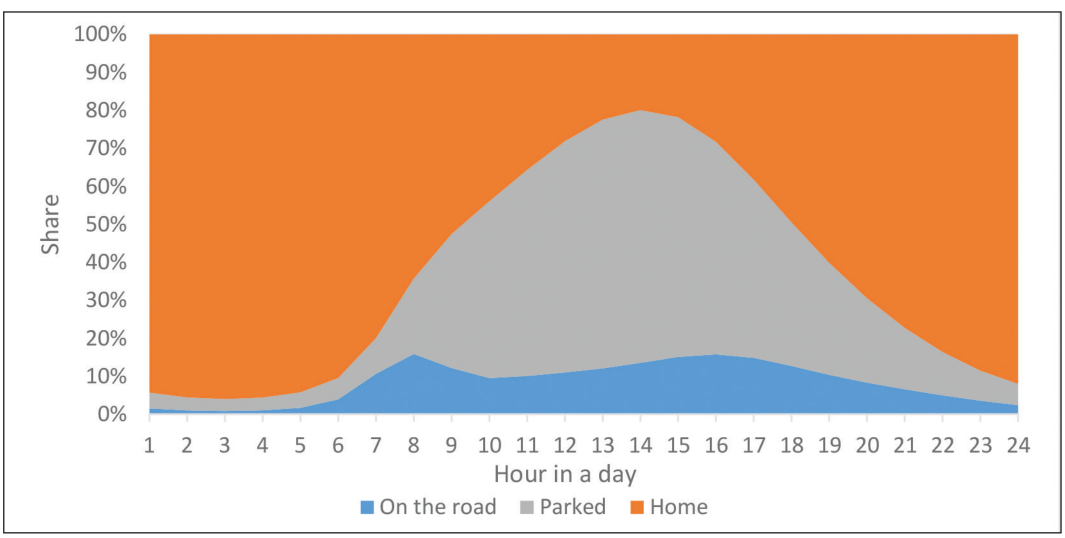

Fig. 5. Hourly vehicle shares by their state during WD

several components can be extracted from travel patterns. In this case, *traffic_work* and *traffic_other*. These components were set as separate demands in a MESSAGE model. See under Final level in Fig. 6.

If all electric vehicles are represented by one technology, then basically everyone shares electric vehicles. When someone completes their journey, someone else can use that car. This is no problem when modelling any other type of vehicles because hourly CO_2 emissions and fuel consumption stays the same no matter if vehicles are shared or not. For EVs, it is a different situation. Electric car charging capacity is related to EV count. If everyone shares vehicles, then total EV count and capacity of all charging units would be very low compared to if they do not share. It significantly affects the charging patterns. For these reasons, groups with different driving patterns should be differentiated and modelled separately. "Car sharing" problem would still exist within the groups but not between them. If the majority of people need to travel at the same time, then this "car sharing" does not affect that much. In principle, the more groups with different driving patterns are modelled, the less of problem "car sharing" is.

Component hourly patterns were set as demand curves for both demands. *traffic_work* and *traffic_other* appear not only in Final level but also in Secondary. There is a requirement in MESSAGE software that producing technology and demand has to be separated by at least one technology in order to apply load regions (term in MESSAGE, which means time subdivisions). *Travel_work* and *Travel_other* technologies connect *traffic_work* and *traffic_other* between Secondary and Final levels. These technologies have

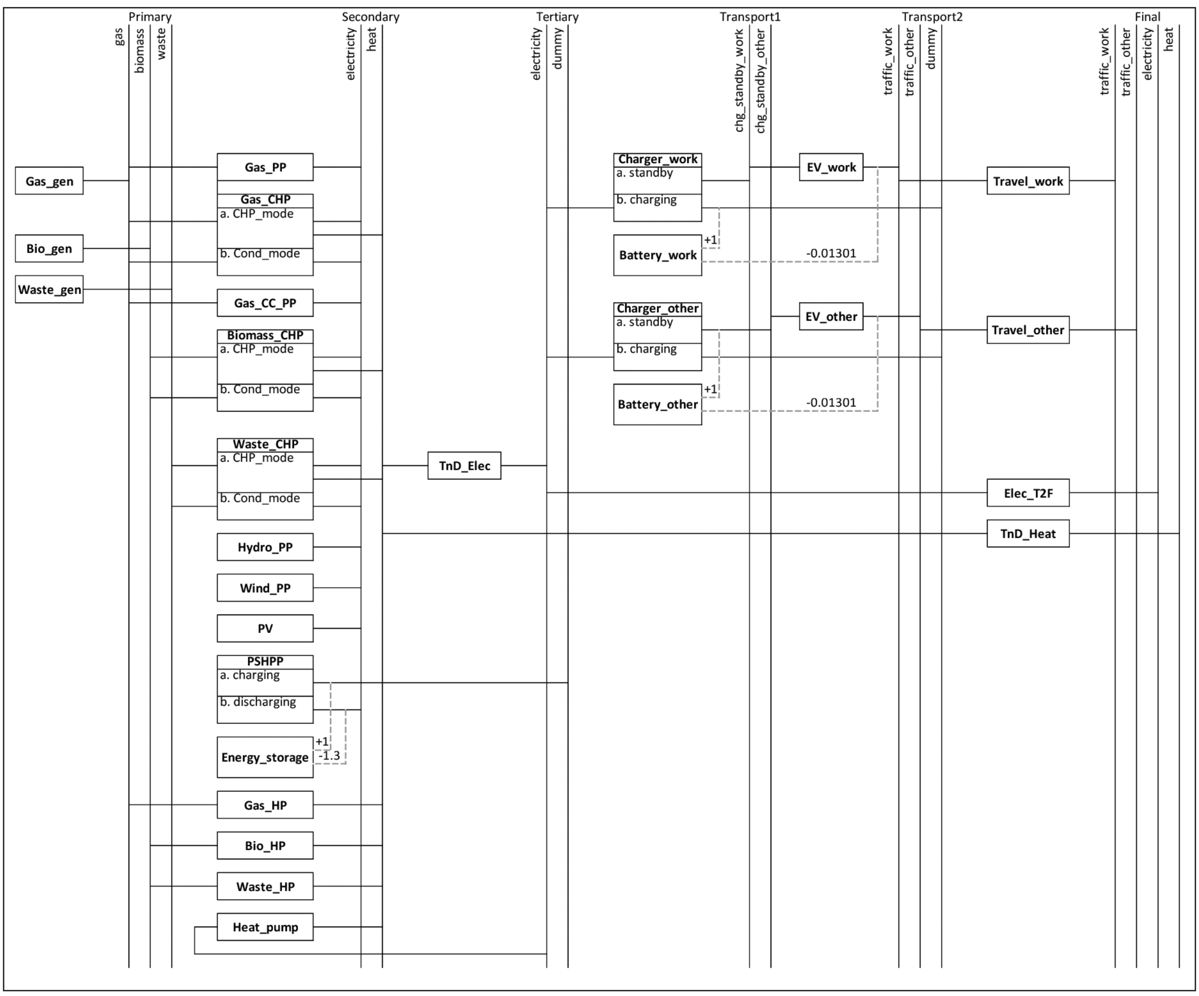

Fig. 6. Electric vehicles in the MESSAGE energy chain

an efficiency of 100% and have no associated costs, thus, they do not affect the results. *traffic_work* and *traffic_other* are produced by corresponding electric vehicle technologies *EV_work* and *EV_other*. Electric vehicles use the stored energy in their batteries (*Battery_work*, *Battery_other*) to charge them. Batteries are charged by *Charger_work* and *Charger_other*. These chargers have 2 alternative activities. The first one is *standby* and the second one is *charging*.

The purpose of *standby* activity is to prevent charging when a vehicle is in use. It produces *chg_strandby_work* or *chg_standby_other* energy form. It represents energy that potentially could have been stored in a battery if charger did not standby. An electric vehicle uses this energy form as input and produces *traffic_work* or *traffic_other* at Secondary level. The efficiency of electric vehicle technology is equal to the ratio between capacities of a single electric vehicle (P_{EV} [Mpkm/yr]) and charger ($P_{charger}$ [MW]):

$$\eta_{EV} = \frac{P_{EV}}{P_{charger}}. \tag{13}$$

The capacity of a single EV is equal to a distance that this vehicle could potentially drive in a year at a set average travel speed ($\bar{v}_{EV}$[km/h]) multiplied by vehicle occupancy rate (VOR):

$$P_{EV} = \frac{\bar{v}_{EV} \cdot 365 \cdot 24 \cdot VOR}{1000000}. \tag{14}$$

It was assumed that average travel speed is 37 km/h, charger capacity is 6.6 kW and average vehicle occupancy is 1.35 passengers, so the capacity of a single EV is 0.4376 Mpkm/yr and efficiency is 66.30.

At this point EVs do not consume any electricity. Energy flows from technology to storage and vice versa in MESSAGE are modelled not through inputs and output, but by using linked storage constraints on activities (*consa*). Set *consa* value shows by how much stored energy increases or decreases (increases if it has a positive sign and decreases if it has a negative one) when one unit of energy is produced in a linked technology. In this case, EV technologies are linked to respective batteries (storages), and *consa* value for both technologies is equal to a negative amount of how many MWyr of electricity are consumed to drive 1 Mpkm:

$$consa = -\frac{1000}{r \cdot 365 \cdot 24 \cdot VOR}. \tag{15}$$

Here: r – a range of electric vehicle in km that can be travelled with 1 kWh.

The second activity of *Charger_work* and *Charger_other* technologies consumes electricity to charge EV batteries. It is assumed that the efficiency of charging is 85%. These activities are linked to respective batteries (storages). *consa* values are set to be equal to 1. This means stored energy is increased by one unit when technology produces one unit of energy. All activities of all technologies in MESSAGE must have at least one output. For this reason, it produces *dummy* energy form, which is not used by any other technology.

A charging curve can be set for the capacity factor, which limits the availability of charging when vehicles are parked not at home. Let us say that all EVs can be charged when at home, but only 20% when they are parked somewhere else. Then capacity factor curves for both components are as in Fig. 7.

When buying an electric vehicle, you also get a home charger for it. The more electric vehicles there are, the higher total charging capacity should be installed. In order to model this relation between the number of cars and total charging capacity installed, an additional equation must be created:

$$C_{charger} - C_{EV}/\eta_{EV} = 0. \tag{16}$$

Here: $C_{charger}$ – total installed charging capacity, C_{EV} – total installed EV capacity.

After implementing this equation, it is possible to address the "car sharing" problem further by adjusting the plant factor of EV technologies. Reduced plant factor results in more vehicles for the same travel demand. Fixed shares between EV and charger capacity ensures that the capacity of chargers would increase with EV installed capacity. However, it also has a negative effect that it allows charging the fleet in a shorter time and thus it can distort charging patterns if set too high, so it should be used with caution. It is recommended to address this problem primarily by distinguishing a higher number of different travel patterns.

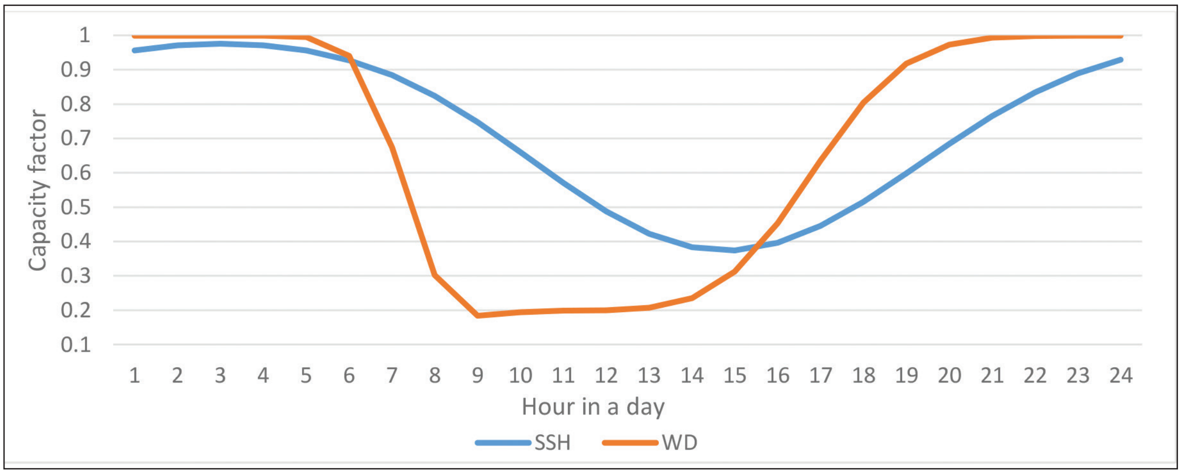

Fig. 7. Capacity factor curves for electric vehicle

RESULTS

The methodology was tested by incorporating the electric vehicles model into a simple model of isolated Lithuanian power and heat sectors. The energy chain of this testing model is presented in Fig. 8. Years 2016, 2020, 2030, 2040,

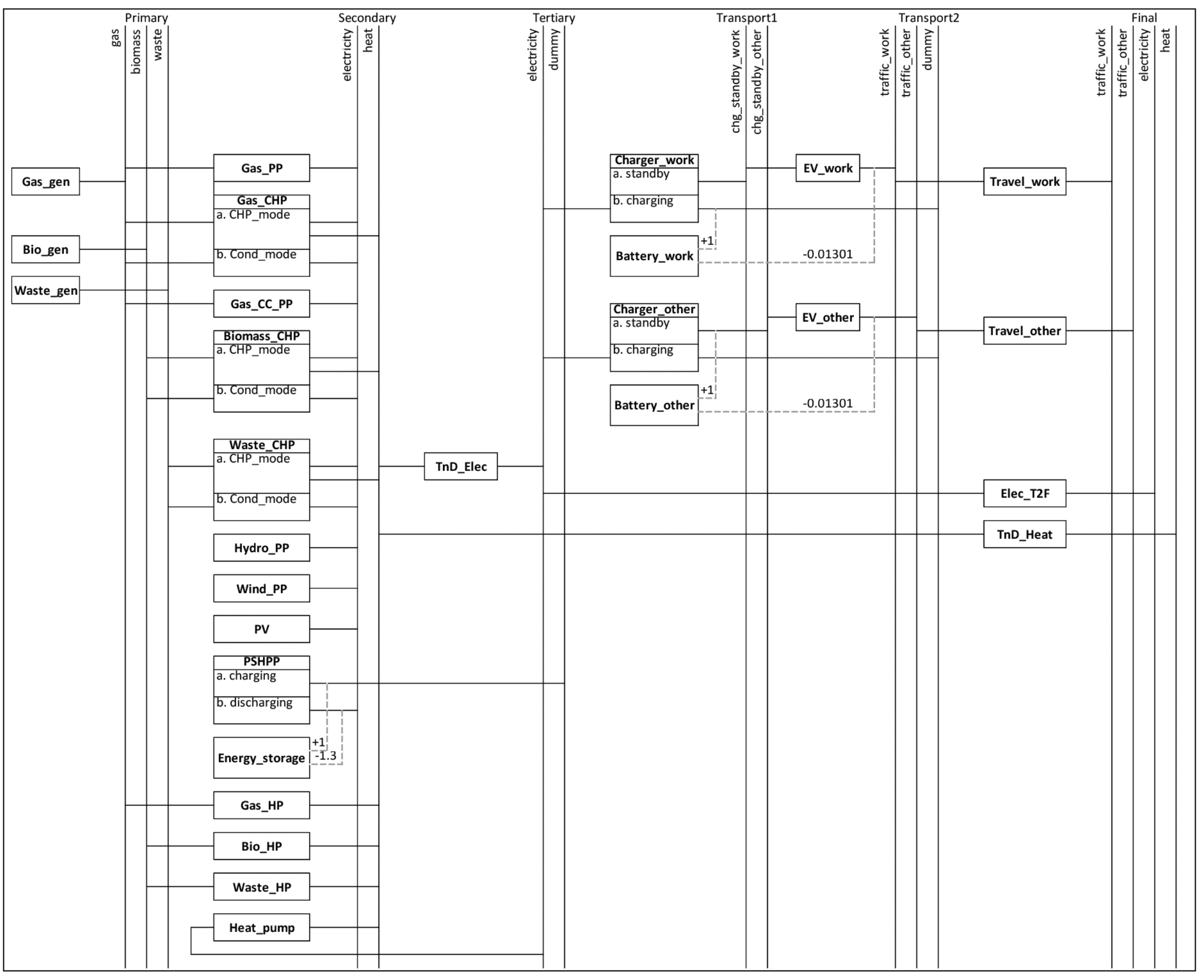

Fig. 8. Energy chain of Lithuanian power and heat sector model with incorporated electric vehicles

2050 were modelled. Each year is divided into 4 seasons, and each season into two typical day types – workdays and SSH. Each day type is divided into 24 hours. Final electricity demand for the year 2016 was set at 1277.516 MWyr with annual growth of 1.49%. District heat demand for 2016 was set at 925 MWyr. It was assumed that heat demand decreases by 1.3% per year. In 2016, 25853.8 million passenger-kilometres were travelled in Lithuania with passenger cars [15]. PKT demands in the model were set in a way so that 10% of this value should be travelled by electric vehicles in 2020, 25% in 2030, 50% in 2040 and 100% in 2050. 81.7% of total PKT demand is of *traffic_other* and 18.3% of *traffic_work*.

It should be mentioned that the results do not represent actual electricity generation shares by the source in Lithuania nor optimal future development pathways. The Lithuanian model was taken from a much bigger Baltic Sea region model and simplified for the demonstration purpose and for testing of this methodology. That being said, annual electricity generation results by technology are given in Fig. 10.

In modelling results, more than 78% of electricity is produced in gas-fired power plants in 2016; however, the share sharply decreases in 2020, because of substantially higher production by wind power plants. Electricity generation from wind increases from 10% in 2016 to 42% in 2020. In 2030 it reduces a bit to 41%. It reaches 45% in 2040 and 48% in 2050. Electricity production from photovoltaics (PV) is below 0.5%, except in 2050, when it reaches 7% (Fig. 10).

Charging patterns of EVs are shown in Fig. 9 for the year 2050 when 100% of PKT demand is satisfied by EVs. From this figure, we can see that the model chooses to charge electric vehicles mostly during the night time. Certainly, capacity factor curves were applied with the lowest values during the daytime, but at the lowest curve point, it was around 0.2 for *traffic_work* and 0.4 for *traffic_other*. In results, the lowest charging output is during 14–15 h ranging from 0 to 10% of installed capacity. Thus, the model was not forced to choose this pattern. The sharp changes show that charging is adjusted to partially absorb electricity production fluctuations from the wind.

In theory, if electricity generation fluctuations can be partially absorbed by adjusting EV charging patterns, then wind penetration in a scenario where EVs are modelled should be higher than in the one where EVs are not modelled. This was tested by creating an additional scenario where demands for PKT were set to be equal to 0. In a period of 2016–2040 results are very similar. In 2050 wind power penetration in the scenario with EVs was higher by 4% (47.7% vs 43.7%); however, PV penetration was higher in the scenario without EVs by 4% (11.1% vs 7.1%). For clarity in this model, only 2 driving patterns were distinguished, thus "car sharing" is a problem for this model; as a result, it affects the flexibility of charging. Furthermore, it was assumed that 20% of the vehicles which are not parked at home can be charged.

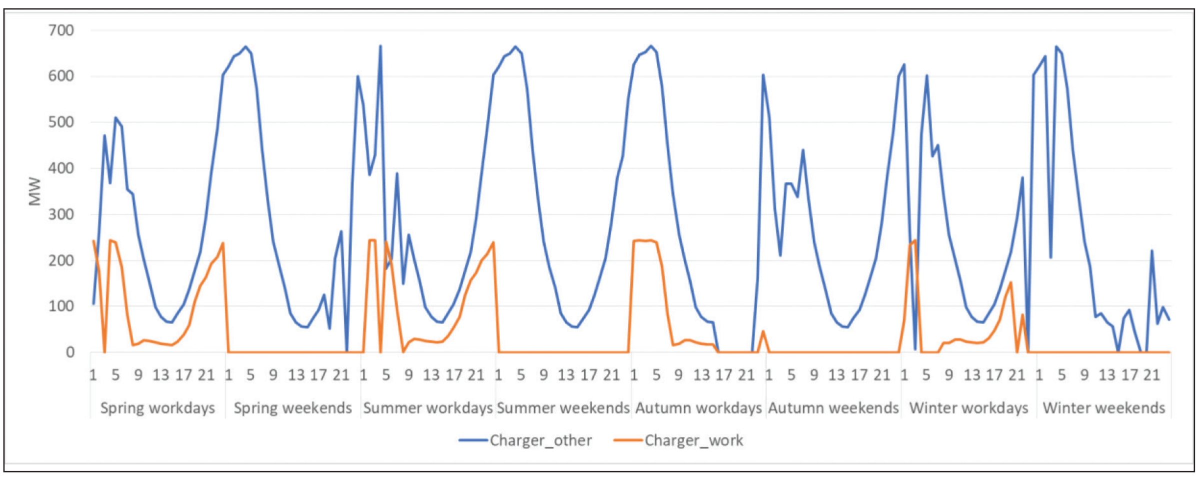

Fig. 9. EV charging patterns in 2050

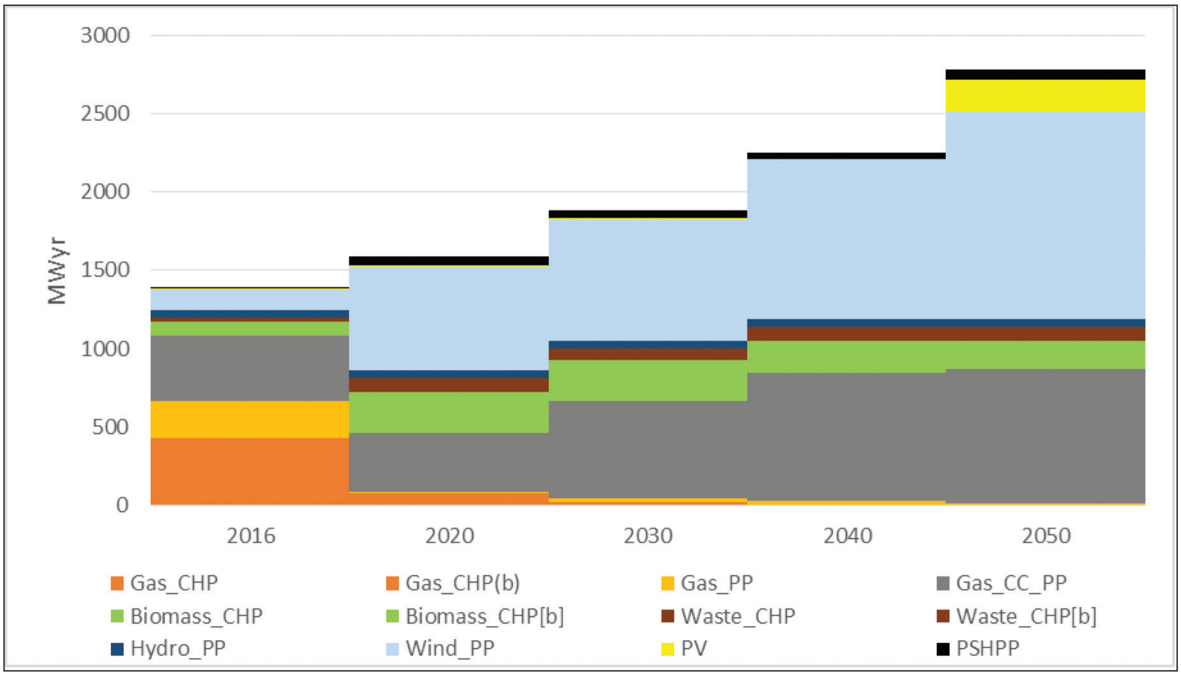

Fig. 10. Modelling results. Annual electricity generation by technologies

CONCLUSIONS

1. When creating an energy planning model, it can be beneficial to use a multisectoral approach due to interconnections between different sectors. Incorporation of the transport sector potentially can be very useful in models where high penetration of renewable energy sources is expected, like decarbonisation models. If it is allowed for the model to endogenously adjust EV charging patterns according to power availability, the model can use charging patterns to increase electricity demand when there is a surplus of energy. The results of this paper show that incorporating EVs in the energy model can result in higher penetration on wind power; however, the same cannot be said for solar power because charging availability during daytime is limited.

2. In order to determine charging availability, it is needed to know whether EVs are being used, parked at home or parked somewhere else at a particular point in time. It is very difficult to acquire such data. Not many studies have been carried out which estimate, categorize and calculate shares of different driving patterns of a whole country, especially of smaller countries like Lithuania. In this paper, a methodology is presented on how driving patterns can be derived from limited data, as passenger flows in public transport, by using pattern approximation with normal distributions.

3. "Car sharing" is a common issue when modelling EVs in energy planning models. It is when a model can satisfy the travel demands of many people with the same vehicle. As a result, fewer vehicles are required to satisfy the demands and, in turn, lower capacity of EV chargers is installed. This issue is unique to EV modelling because fuel balances are not affected by it. "Car sharing" issue can be reduced by differentiating a larger number of different driving patterns. Vehicle sharing is limited when the majority needs to drive at the same time. Unique travel demands should be defined for each driving pattern. Unique travel demands should be satisfied with different EV technologies, which have their own charging technologies and energy storage. If the rest of the transport sector is also modelled, then for each other vehicle type only single technology is needed, which should be connected to multiple travel demands.

4. In this paper it is explained in detail how EVs can be modelled in MESSAGE software; however, this approach is not limited only to MESSAGE. With some modifications, it can be implemented

in TIMES, Balmorel and other modelling software.

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Eimantas Neniškis

ELEKTROMOBILIŲ MODELIAVIMAS IR JŲ ĮKROVIMO KREIVIŲ NUSTATYMAS ENDOGENIŠKAI ENERGETIKOS PLANAVIMO MODELIUOSE

Santrauka

Naujausi moksliniai tyrimai apie klimato kaitą atskleidžia, kad priemonės, numatytos Paryžiaus susitarime dėl klimato kaitos, nėra pakankamos siekiant apriboti vidutinės temperatūros pasaulyje augimą iki 2 °C, palyginti su priešindustriniu laikotarpiu. Turėtų būti keliami ambicingesni tikslai. Tokiems tikslams pasiekti yra būtini kompleksiniai tarpsektoriniai modeliai, kuriais būtų galima nustatyti tinkamiausius ekonomikos dekarbonizacijos būdus. Elektromobiliai potencialiai gali reikšmingai sumažinti anglies dvideginio emisijas transporto sektoriuje. Kaip žinoma, elektromobilių akumuliatoriams įkrauti yra būtina elektros energija, dėl ko didėtų ir bendras elektros energijos poreikis. Dėl elektromobilių emisijų sumažėjimas transporto sektoriuje gali būti atsvertas padidėjusia gamyba iškastinį kurą naudojančiose elektrinėse, siekiant užtikrinti reikalingą papildomą energijos kiekį. Kita vertus, reguliuojant įkrovimą galima balansuoti gamybos iš atsinaujinančių energijos išteklių pikus, o tai leistų užtikrinti didesnę atsinaujinančių išteklių skvarbą. Dėl šių priežasčių naudinga įtraukti elektromobilius į energetikos planavimo modelius, ypač į tuos, kuriais yra mėginama įvertinti galimus dekarbonizacijos būdus.

Straipsnyje pateikta elektromobilių modeliavimo metodika energetikos planavimo modeliuose. Šioje modeliavimo metodikoje, atsižvelgiant į elektros gamybą, modelis pats nustato elektromobilių įkrovimo kreives. Metodika yra grįsta skirtingų automobilio išvykimo ir sugrįžimo laikų išskyrimu ir skirtingų automobilio būsenų įvertinimu. Straipsnyje taip pat aprašoma, kaip turint ribotus duomenis ir naudojant kelionių kreivės aproksimaciją normaliaisiais skirstiniais nustatomi išvykimo ir sugrįžimo laikai.

Raktažodžiai: elektromobiliai, įkrovimas, endogeniškumas, energetikos planavimas, MESSAGE