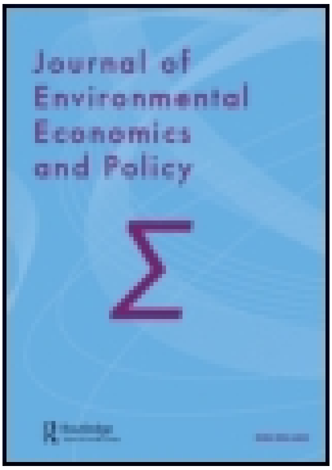

Journal of Environmental Economics and Policy

Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/teep20

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Published online: 12 Mar 2015.

Journal of Environmental Economics and Policy, 2015
http://dx.doi.org/10.1080/21606544.2015.1019569

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Economic and environmental multi-objective optimisation to evaluate the impact of Belgian policy on solar power and electric vehicles

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(*Received 8 October 2014; accepted 11 February 2015*)

This research uses multi-objective optimisation to determine the optimal mixture of energy and transportation technologies, while optimising economic and environmental impacts. We demonstrate the added value of using multi-objective mixed integer linear programming (MOMILP) considering economies of scale versus using continuous multi-objective linear programming assuming average cost intervals. This paper uses an improved version to solve MOMILPs exactly. To differentiate optimal solutions with and without subsidies, the impact of policy on the Pareto frontier is assessed. We distinguish between minimising economic life cycle costs (complete rationality) and required investments (bounded rationality). The approach is illustrated using a Belgian company with demands for electricity and transport. Electricity technologies are solar photovoltaics and the grid; transportation includes internal combustion engine vehicles, grid powered battery electric vehicles (BEVs), and solar-powered BEVs. The impact of grid powered BEVs to reduce GHG emissions is limited, yet they are less costly than solar panels to decrease emissions. Current policy measures are found to be properly targeting rational investors who consider life cycle costs, while private (potentially bounded rational) investors often focus on required investments only.

Keywords: mixed integer programming; branch and bound; energy; transport; LCC; LCA

1. Introduction

In the light of climate change, Europe has put in place legislation to reduce greenhouse gas (GHG) emissions to 20% below 1990 levels by 2020 (European Commission 2009). In 2010, the combined share of electricity and heat generation and transport represented nearly two-thirds of global emissions (International Energy Agency 2012). Recognising that the former sectors are the world's largest contributors to climate change, the use of clean energy sources and alternative transportation technologies is widely stimulated. Better environmental performances often imply a trade-off with increased economic costs. Hence, clean energy and transportation technologies require assessments from both an economic and environmental point of view. A possible way to address this is combining economic costs and environmental impacts into a mitigation assessment (Sathaye and Meyers 1995), and calculating the technologies' cost for mitigation accordingly. This methodology allows ranking different technologies or projects in order of increasing cost

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of emission abatement. Amongst others, this approach has been demonstrated by De Schepper et al. (2014), who developed a framework to compare energy and transportation technologies in terms of cost-efficient GHG emission reduction. One drawback however is that the mitigation cost assessment is always dependent on a baseline or reference technology (Sathaye and Meyers 1995). Moreover, as assumptions regarding the baseline affect both the additional costs and the reduced emissions of the implemented technology, a technology's mitigation cost can vary widely depending on the baseline chosen. A second shortcoming is that while the mitigation cost clearly indicates the cost per ton of emissions avoided for each separate technology, it does not provide any information on determining an optimal mixture of different technologies to satisfy required demands. In this research, we propose to overcome these drawbacks by means of a multi-objective optimisation approach.

Multi-objective optimisation or MOO is an area of multiple criteria decision-making that is concerned with the mathematical optimisation of multiple objective functions, subject to a set of constraints. The use of MOO is of particular interest when optimal decisions need to be taken in the presence of trade-offs between conflicting objectives, in which case plural optimal solutions exist. In literature, we find numerous examples regarding the use of MOO to determine the optimal mix of energy technologies within an energy system. A review of the use of multi-criteria approaches in energy systems has been provided in Wang et al. (2009). In a basic form, energy systems are limited to the generation of electricity. For example, in Arnette and Zobel (2012), a multi-objective model is developed to determine the optimal mix of renewable energy sources and existing fossil fuel facilities on a regional basis, considering generation costs and GHG emissions. In a more complex form, energy systems may include other generation technologies besides electricity such as heating or co-production technologies, implying a more complicated MOO model to determine the optimal design of the system (Liu, Pistikopoulos, and Li 2010). MOO has been extensively used to determine the optimal mixture of energy (e.g. electricity and heat generating) technologies. However, to the best of the authors' knowledge, it has not been applied yet to find the optimal mix of energy and transportation technologies. Nonetheless, we argue that it is valuable to consider energy and transportation simultaneously, for three main reasons. (1) These are the world's two most polluting sectors (International Energy Agency 2012); (2) nearly all entities (e.g. multinationals, small- and medium-sized enterprises or SMEs, households, etc.) have needs regarding both; (3) when combined, synergies might be exploited such as additional emission reduction (Doucette and McCulloch 2011) and diminishment of the effect of power variability of intermittent clean energy sources such as solar photovoltaics (PV) (Zhang et al. 2012) or wind power (Hennings, Mischinger, and Linssen 2013; Liu et al. 2013). A large deployment of renewable sources could lead to curtailments, power drops and thus a general inefficiency and unreliability of the entire power system (Fattori, Anglani, and Muliere 2014). The rise of distributed, intermittent clean energy sources calls for a novel change in the way we conceive electricity production and distribution. With a growing share of dispersed, renewable energy generation, the distribution networks will have to change from being passive into active (smart) systems as electricity will no longer be passed on using a hierarchical top−down flow from the electricity plant towards the end consumer. In such a system, distributed generation installations are managed as a virtual power plant by a control entity, which regulates the output. Combining different technologies, of which some are able to produce electricity on demand, should allow smoothing the stochastic supply. It has long been recognised that battery electric vehicles (BEVs) can not only be used as a transport means but also for electricity storage and generation (Kempton and Letendre 1997). BEVs, thus, offer the additional advantage of being able to provide electricity on demand and able to serve as a dynamic load. For a review on the latest research and advancements of BEV interaction with smart grids, we kindly refer the reader to Mwasilu et al. (2014).

In this research, we use MOO to determine the optimal mixture of electricity and transportation technologies given required energy and transportation needs, while optimising economic and environmental performances. To obtain realistic results, economies of scale-cost advantages that enterprises obtain with increasing scale (Pindyck and Rubinfeld 2009, 245−247) are considered. This inherently discrete phenomenon implies the use of mixed integer programming (Mavrotas et al. 2008). We demonstrate the added value of using multi-objective mixed integer linear programming (MOMILP) considering economies of scale versus using continuous multi-objective linear programming (MOLP) assuming average cost intervals. This research applies the improved version of the exact multiple objective branch and bound algorithm for mixed 0−1 linear programming as described in Vincent et al. (2013). To the best of our knowledge, this algorithm is the only method available to find all the optimal solutions of a MOMILP problem exactly; other attempts found in literature provide an approximation of the optimal solution frontier. For example, Arnette and Zobel (2012) propose a MOMILP optimisation model for renewable energy development and they approximate the optimal solution frontier by means of a linear relaxation of five supported solutions. Furthermore, we point to the impact of policy measures. The global energy sector receives among the highest financial support provided to any sector of the global economy (Badcock and Lenzen 2010). Likewise, policymakers provide strong financial incentives for sustainable road transport (Santos, Behrendt, and Teytelboym 2010). To distinguish between the optimal solutions with and without subsidies and taxes, we visualise the impact of policy on the Pareto frontier. Finally, we compare minimising full economic life cycle costs (including initial investment as well as operation costs) and minimising solely the initial investments. Moreover, in complex and uncertain circumstances, humans make decisions under the constraints of limited knowledge, resources, and time; which is defined as 'bounded rationality' (Gigerenzer and Selten 2002). Hence, a comparison is made between completely rational versus bounded-rational investors. The approach is illustrated with a Belgian SME seeking to find the optimal combination of technologies to satisfy electricity and transportation demands, while minimising environmental emissions and economic costs.

In Section 1, we discussed the need for using an MOO approach to find the optimal mixture of electricity and transport technologies considering economic and environmental objectives. In the following section, the optimisation model is discussed. Section 3 elaborates on the solution method. In Section 4, the results of the case and the limitations of the model are discussed. The paper ends with a conclusion of the findings including policy implications in Section 5.

2. Optimisation model

2.1. Basic model

The aim of this basic model is to mathematically represent the optimisation of the combined use of n different technologies of the same type (e.g. energy-generating technologies or transportation technologies) from an economic and environmental point of view. Consider the case of energy-generating technologies (transportation is analogous). The decision variables x_i represent the proportion of technology i used in the combination of energy generating technologies. The two competing objectives in the model are to minimise (1) economic costs and (2) environmental emissions. Note that the use of energy and transport technologies implies the occurrence of costs, yet in most cases it does not provide direct revenues. Therefore, our research objectives focus on cost minimisation rather than on profit maximisation. Nonetheless, if any kind of income (e.g. subsidies) is provided, this is to be deducted from the project costs. The economic costs (e.g. initial investment, operating and maintenance costs, taxes) and environmental emissions (e.g. GHG emissions) implied by one unit of technology i are represented respectively by means of the data c_i^1 and c_i^2. The economic coefficient c_i^1 is calculated using life cycle costing (LCC), which is an assessment technique that takes into consideration all the cost factors relating to the asset during its operational life. For purposes of comparison, we also calculate the economic costs considering exclusively the initial investment, which can be of importance for bounded-rational investors. Data regarding the required investment will be summarised in the coefficient c_i^1. In both the fully rational and the bounded-rational case, a net present value approach is used to calculate costs. The environmental coefficient c_i^2 can be determined using life cycle analysis (LCA), a tool to assess environmental impacts of complete life cycles of products or functions. Furthermore, a required energy demand d – determined according to the investor's preferences – has to be satisfied. In this constraint, q_i is defined as the amount of energy provided by one unit of technology i. Hence, assuming linear relations, the optimisation of the use of technologies i to satisfy required demand d can be formulated as an MOLP problem as follows:

$$\text{Min} \sum_{i=1}^{n} c_i^1 x_i \quad \text{Economic objective function}$$

$$\text{Min} \sum_{i=1}^{n} c_i^2 x_i \quad \text{Environmental objective function}$$

$$\text{Subject to} \sum_{i=1}^{n} q_i \, x_i = d \quad \text{Satisfy demand constraint}$$

$$x \in X$$

$$X \subset R_+^n.$$

2.2. Economies of scale

Due to the existence of economies of scale, the technology unit cost to be paid by the investor may vary for different technology sizes. Accordingly, technology i should be subdivided into k intervals, each having a lower and upper bound. Furthermore, to indicate the interval k that is active for technology i, binary variables y_{ik} (with value 0 or 1) need to be introduced in the developed MOLP, turning the latter into an MOMILP problem. Hence, the previous model should be adapted as follows.

Variables x_{ik} and y_{ik} are added to the model, implying the following constraints:

$$\sum_{k \in \text{interval } i} x_{ik} = x_i \;\; \forall\, i = 1, \ldots, n \quad \text{Each technology } x_i \text{ subdivided in } k \text{ intervals}$$

$$\sum_{k \in \text{interval } i} y_{ik} = 1 \;\; \forall i = 1, \ldots, n \quad \text{Exactly one interval active for technology } x_{ik}.$$

The variables x_{ik} are bounded by the following constraint, which ensures that $x_{ik} = 0$, if its associated interval is not active ($y_{ik} = 0$):

$$lb_{ik}y_{ik} \leq w_{ik}x_{ik} \leq ub_{ik}y_{ik} \quad \text{Lower and upper bound interval } k \text{ of technology } i \quad \forall\ i = 1, \ldots, n; k \in \text{interval } i.$$

Finally, the objective functions are the following:

$$\text{Min} \sum_{i=1}^{n} \sum_{k \in \text{interval } i} c^1_{ik}x_{ik} \quad \text{Economic objective function}$$

$$\text{Min} \sum_{i=1}^{n} \sum_{k \in \text{interval } i} c^2_{ik}x_{ik} \quad \text{Environmental objective function.}$$

2.3. Energy versus transportation technologies

In this paper, we develop a model that allows comparing energy generating technologies versus transportation technologies, the latter being possibly energy consuming. To this end, we need to explicitly distinguish between variables and data regarding energy technologies E on the one hand, and transportation technologies T on the other. Moreover, an additional demand (for transportation) has to be satisfied. Accordingly, the following variables and data need to be split:

$$x = \begin{bmatrix} x_E \\ x_T \end{bmatrix}, \quad Q = \begin{bmatrix} q_E^T \\ q_T^T \end{bmatrix}, \quad d = \begin{bmatrix} d_E \\ d_T \end{bmatrix}.$$

We specify the number of technologies n, assuming m energy generating and p transport technologies:

$$x_E = \begin{bmatrix} x_{E_1} \\ x_{E_2} \\ \cdots \\ x_{E_m} \end{bmatrix} \quad \text{and} \quad x_T = \begin{bmatrix} x_{T_1} \\ x_{T_2} \\ \cdots \\ x_{T_p} \end{bmatrix}.$$

Hence, considering energy and transportation technologies simultaneously leads to the following demand constraints:

$$\sum_{i \varepsilon E} q_i x_i = d_E \quad \text{Satisfy energy demand constraint}$$

$$\sum_{i \varepsilon T} q_i x_i = d_T \quad \text{Satisfy transportation demand constraint.}$$

Finally, an additional set of constraints that allows linking energy generating and transportation technologies must be added to the MOMILP. Accordingly, factor e_{ij} is introduced, representing the quantity of energy technology i required to supply one unit of transportation technology j. Let $PoweredBy_i$ with $i \in E$ be the set of transportation technologies j that can be powered by i. We assume that two different energy technologies i and i' cannot supply the same transportation technology j. It hence implies the

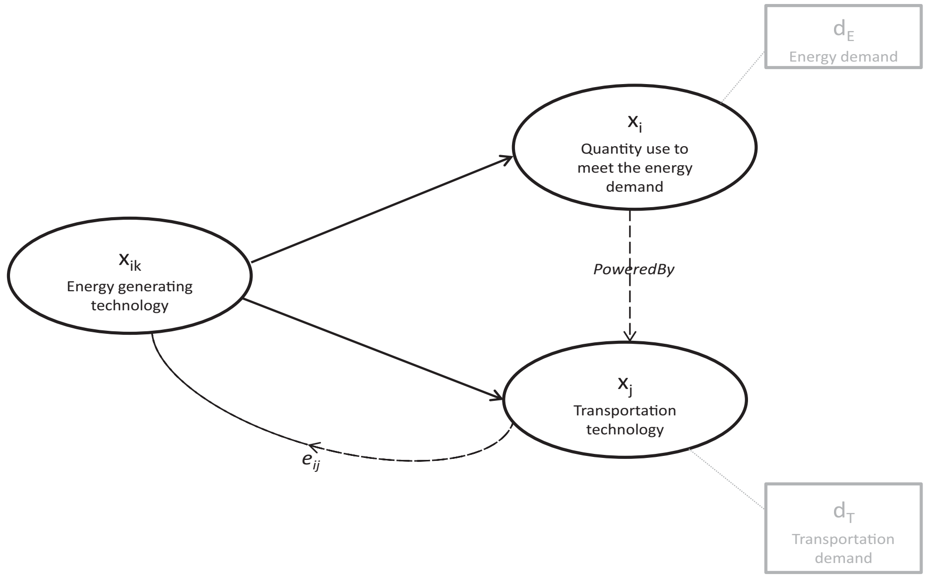

Figure 1. Schematic representation of the link between energy and transportation technologies.

following constraints:

$$\forall i \in E: \sum_{k \,\in\, \text{Interval}_i} x_{ik} = x_i + \sum_{j \,\in\, PoweredBy_i} e_{ij} x_j \quad \text{Total amount of energy generation}$$

$$\forall i \in T: \sum_{k \,\in\, \text{Interval}_i} x_{ik} = x_i \quad \text{Total amount of transportation.}$$

The linking of energy and transportation technologies is represented schematically in Figure 1. The transport technologies (x_j) require an amount of energy to be fueled, which is given using the relation *'PoweredBy'*. The coefficient e_{ij} transforms the amount of transportation technology j into a corresponding amount of energy technology i. Note, however, that the demand for energy (d_E) is not increased due to this energy consumption of the vehicles. Consequently, x_{ik} comprises both the amount of energy technology i used to fulfil energy demand d_E and the amount of energy used to power the transport technologies j. We note that for energy technologies the interval k is related to the capacity of the system, as the unit cost decreases with larger capacities due to economies of scale. For transportation technologies, k is related to the amount of vehicles as quantity reductions can be obtained from vehicle distributors. Quantity reductions refer to discounts that can be obtained when purchasing larger quantities at once.

3. Solution method

In this research, we use a multi-objective branch and bound algorithm developed by Mavrotas and Diakoulaki (1998, 2005) and recently improved and corrected for the bi-objective case by Vincent et al. (2013) (Figure 2). This algorithm aims at finding all the efficient solutions of MOMILPs exactly. As per definition, an efficient or Pareto optimal solution is a feasible solution that is not dominated by any other feasible solution (i.e. no

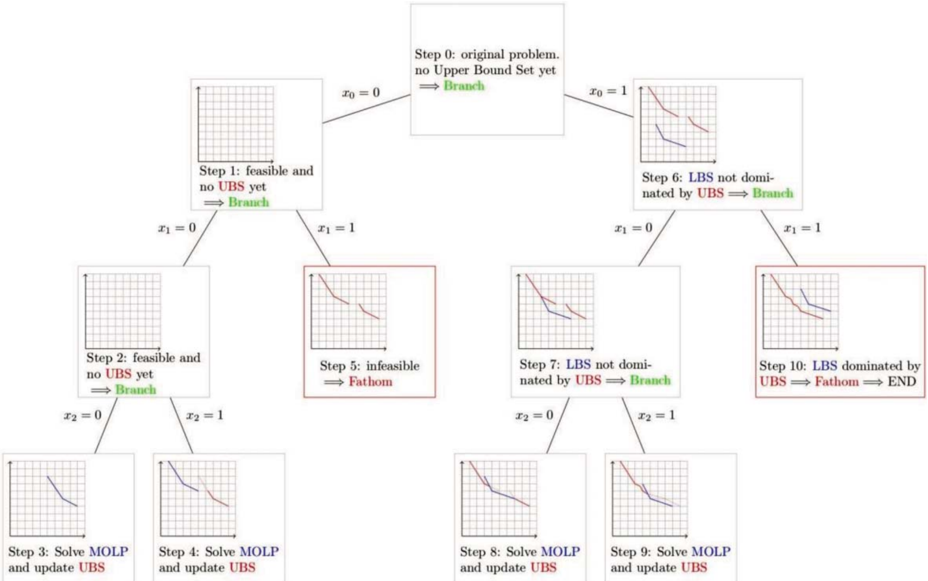

Figure 2. Tree exploration within the exact multi-objective branch and bound algorithm for the bi-objective case as developed by Mavrotas and Diakoulaki (1998, 2005) and improved and corrected by Vincent et al. (2013).

other solution performs better on all the objectives at the same time). The developed branch and bound algorithm explores a binary tree, i.e. a tree which enumerates all the possible combinations of values for the binary variables. The algorithm starts at the root node; the ancestor of all nodes that represents the original problem (Figure 2, step 0). Then it visits the tree following a depth-first search scheme. All other nodes of the tree represent a sub-problem where some of the binaries have been fixed. The binary variables which have not been fixed yet are called free variables. At any stage of the algorithm, a list of solutions called the incumbent list is updated by storing all the potentially efficient solutions. The incumbent list is initially empty and it is updated whenever a final node or 'leaf node' is visited. In such a node, all the binary variables are fixed and hence, the corresponding sub-problem is a simple MOLP. This MOLP is then solved using a multi-objective simplex and if the solutions are efficient to the global problem, they are added to the incumbent list. Additionally, the incumbent list serves the role of upper bound set (UBS) on the global problem. Hence, only the solutions that are not dominated by this UBS are potentially efficient.

We note that the binary tree grows exponentially with the number of binary variables. Moreover, given n binary variables, the binary tree consists of 2^{n+1} nodes. Fortunately, the algorithm allows to discard nodes (either by infeasibility or by dominance), and hence it is not necessary to explore all nodes. When a node is visited, the linear relaxation of the according sub-problem is considered, i.e. the free binary variables are temporarily supposed continuous in the interval [0,1]. This linear relaxation can either be feasible or infeasible. If it is infeasible, the node is discarded by infeasibility (e.g. step 5); if it is feasible, a lower bound set (LBS) of the linear relaxation is computed. This LBS represents an optimistic evaluation of the solution set that can be obtained from the current node and it is compared to the UBS of the global problem. If at least a part of the LBS is dominated by the UBS (e.g. step 10), the node can be discarded by dominance. If the LBS is not dominated by the UBS (e.g. step 6), the node is not discarded and its child nodes are generated by fixing one additional binary variable at a time. These child nodes must be explored as well. At the termination of the algorithm, the incumbent list contains all the efficient solutions.

Vincent et al. (2013) proposed a new representation of the solution set for the bi-objective case to correct errors that lead to keeping dominated solutions. Furthermore, the authors introduced the use of an actual LBS instead of a single lower bound point, allowing to discard nodes more efficiently. Another improvement is a preprocessing that determines in which order the variables should be fixed. This allows the algorithm to find good solutions sooner, leading to a better discarding, less visits of nodes and thus reduced solution times.

4. Case study

4.1. Model formulation

We studied a small steel processing company in Flanders with a specific annual demand for electricity and transportation. To fulfil electricity needs, the firm has two technologies at hand: (1) grid electricity (which is already in place, i.e. grid electricity is their current manner of obtaining electricity) and (2) roof mounted photovoltaic solar panels. They are interested in PV in particular because they have a large, optimally oriented roof area available to install PV panels and because the installation of this solar project does not require the lengthy, often expensive process of filing for an official permission, which would be the case for alternative energy technologies such as wind mills. For transportation and more particularly, for the commuting of their staff, the company considers three different types of vehicles: (1) gasoline powered internal combustion engine vehicles (ICEVs) (their current vehicles), (2) grid powered BEVs and (3) solar-powered BEVs. The latter technology exemplifies the concept of electric vehicle workplace charging using PV panels (Tulpule et al. 2013). Moreover, the company considers a simple grid-connected solar PV parking structure for their BEVs at the main entrance of their buildings to enhance the visibility of their corporate environmental responsibility strategy. The vehicles are all comparable in size, i.e. medium-sized vehicles for the commuting of employees. Note that we do not consider diesel vehicles; currently the SME only uses gasoline ICEVs as travel distances are relatively short. This renders BEVs with limited driving ranges an interesting alternative. The company considers BEVs for transport because they prefer ‘zero-emission’ vehicles that they can easily power with electricity that is available on their site, which would not be the case for alternative clean transport technologies such as hydrogen vehicles. One could argue that an alternative strategy for the company to minimise economic costs and environmental emissions could be to trade CO_2 permits under the European Union’s Emissions Trading System (EU ETS). However, the steel company only monitors the emissions that are required by law, i.e. emissions that are directly related to their installations including emissions of the raw materials, conventional fuels, process gases, consumption of graphite electrodes, other fuels and waste gas scrubbing (European Commission 2012). Hence, the emissions of electricity for their offices and transport for their staff are not monitored under their EU ETS compliance. Therefore, we do not consider the purchase of tradable CO_2 permits as an alternative option to decrease costs and emissions. We acknowledge that the results of

Table 1. Decision variables x_{ijk}.

Energy versus transportation technology		Type of technology		Number of intervals for each technology (economies of scale)	
$i = 1$	Electricity	$j = 0$	Grid	$k = 1$	One interval
		$j = 1$	PV	$k = 1, 2, \ldots 7$	Seven intervals
$i = 2$	Vehicles	$j = 0$	ICEV	$k = 1, 2, 3$	Three intervals
		$j = 1$	Grid BEV	$k = 1, 2, 3$	Three intervals
		$j = 2$	Solar BEV	$k = 1, 2, 3$	Three intervals

the study are case and situation specific, yet the proposed methodology is applicable to other cases in which economies of scale are present.

4.1.1. Decision variables

From the model presented in Section 2, we redefine the decision variables x_{ik} by distinguishing energy generating and transportation technologies. This leads to the variables x_{ijk} as defined in Table 1.

In addition, we note that the variables that represent the same type of technology are measured in the same unit. In this paper, we use kilowatt-hours per year (kWh/y) for energy generating technologies, and kilometres per year (km/y) for transportation technologies. The data are then normalised with respect to the annual demand for energy and transport. For example, considering the use of solar panels for electricity generation (i.e. $i = 1, j = 1$), we first assess the annual amount of solar electricity generated (kWh/y). Next, we normalise this amount with respect to the total annual energy demand (kWh/y). Therefore, x_{ijk} takes a value within the interval [0,1] and hence represents the portion of annual demand d covered by technology j, in interval k. This normalisation allows describing the mix of technologies used to satisfy demand d. For instance, $x_{11k} = 0.5$ implies that 50% of the electricity demand is covered by means of solar panels. The Boolean variable y_{ijk} represents the activity of interval k − given the corresponding level of economies of scale − for technology j of type i.

4.1.2. Objective functions

4.1.2.1. Economic objective function. The economic costs of the technologies are calculated using LCC. We assume that the lifetime of the project equals the lifetime of the 'longest living' technology; that is solar PV with a lifetime of 20 years (data in Table 2). Technologies should always be compared over the same discounting period so that they have the same opportunity to accumulate costs and benefits. In this paper, we use the rollover method to compare projects with unequal lifetimes (Boardman et al. 2011), i.e. the project with the shorter lifetime is 'rolled over' within the lifetime of the longer project: given technology T_s with short lifetime n_{Ts} that needs to be compared with technology T_l with longer lifetime n_{Tl}, the number of times that technology T_s needs to be 'rolled over' (z) is given in Equation (1). The calculation of the initial unit cost of the required investment in T_s (UC_{Ts}) is then calculated according to Equation (2), by taking into account the real annual price evolution of the technologies ($\dot{P}$), and then discounting at discount rate r. Hence, given a vehicle lifetime of 5 years, the investment in the vehicles is 'rolled over'

Table 2. Case study: data economic costs; parameter values excluding and including policy measures.

Parameter	Symbol	Value excl. policy	Value incl. policy	Motivation
General				
Tax rate	t_r	0%	33.99%	(FOD Financiën 1992)
Discount rate	r	4%	Idem	(European Commission 2009)
Annual electricity need	d_E	150,000 kWh/y; 190.47 kWp (P_{tot})	Idem	SME's electricity need
Transportation need	d_T	14,996.27 km/y/veh; 8 vehicles (V);	Idem	SME's transportation need
Lifetime	n	20 y	Idem	Lifetime of the longest living technology, i.e. solar PV
Solar PV installation				
Irradiation factor	B	850 kWh/kWp	Idem	(Súri et al. 2007)
Annual PV deterioration rate	A	0.70%/y	Idem	Four Belgian PV companies
Lifetime	n_{PV}	20 y	Idem	Four Belgian PV companies
Unit cost in function of PV capacity	UC_{PV}	If $0 < P_{tot} < 11.5$ kWp:2150 €/kWp If $11.5 < P_{tot} < 25$ kWp:2150 €/kWp If $25 < P_{tot} < 50$ kWp:2100 €/kWp If $50 < P_{tot} < 100$ kWp:1900 €/kWp If $100 < P_{tot} < 200$ kWp:1600 €/kWp If $200 < P_{tot} < 300$ kWp:1400 €/kWp If $P_{tot} > 300$ kWp:1300 €/kWp	Idem 2250 €/kWp Idem Idem Idem Idem Idem	Average initial unit cost of PV depends on the total power of the installation; numerical values according to four Belgian companies. For installations exceeding 11.5 kWp, legislation imposes the additional costs of a grid study, an electricity meter, metre, and a decoupling box. For larger installations the unit cost decreases due to economies of scale
Annual insurance cost	$INSC_{PV}$	0.23% of PV investment cost	Idem	Four Belgian PV companies
Annual maintenance cost	MC_{PV}	11 €/kWp	Idem	Four Belgian PV companies
Tradable green certificates	TGC	0 €/kWh	0.093 €/kWh	(Flemish Energy Agency 2013)
Lifetime tradable green certificates	n_{TGC}	0 y	10 y	(Flemish Energy Agency 2013)
Elevated investment deduction	$EID_{\%}$	0% of PV investment cost	15.50%	(Flemish Energy Agency 2013)

(*continued*)

Table 2. (*continued*)

Parameter	Symbol	Value excl. policy	Value incl. policy	Motivation
Grid				
Unit cost electricity	UC_{electr}	0€	Idem	Grid available at the site
Electricity price	P_{electr}	0.093 €/kWh	0.095 €/kWh	(Eurostat 2012)
Annual evolution electricity price	$\dot{P}_{Electr}$	1.76%/y	Idem	(Eurostat 2012)
Grid powered battery electric vehicle, Nissan Leaf (grid BEV)				
Lifetime	n_{BEV}	5 y	Idem	Average lifetime of a company car in Belgium
Unit cost	UC_{grBEV}	29,194 € for 0 < vehicles < 5 28,430 € for 5 < vehicles < 50 27,818 € for >50 vehicles	Idem Idem Idem	Unit cost (Nissan 2013a); quantity reductions according to two Belgian Nissan distributors
Annual price evolution	$\dot{P}_{BEV}$	−5.39%/y	Idem	(Weiss et al. 2012; EU Coalition−McKinsey 2010)
Fuel use	$Fuse_{BEV}$	0.173 kWh/km	Idem	(Nissan 2013b)
Electricity price	P_{electr}	0.093 €/kWh	0.095 €/kWh	(Eurostat 2012)
Annual evolution electricity price	$\dot{P}_{Electr}$	1.76%/y	Idem	(Eurostat 2012)
Maintenance cost	MC_{grBEV}	266.4 €/veh/y	Idem	Two Belgian Nissan distributors
Vehicle registration tax	T_{oBEV}	0 €	Idem	(FOD Financiën 2013b)
Price evolution registration tax	$\dot{P}_{ToBEV}$	0%/y	Idem	Geometric mean 2005−2012 (FOD Financiën 2013a)
Annual traffic tax	T_{nBEV}	0€/y	75.77 €/y	(FOD Financiën 2013b)
Price evolution traffic tax	$\dot{P}_{TnBEV}$	0%/y	2.31%/y	Geometric mean 2005−2012 (FOD Financiën 2013a)
Investment deduction	$ID\%_{BEV}$	0%	120%	(Belgisch Staatsblad 2009)

(*continued*)

Table 2. (*continued*)

Parameter	Symbol	Value excl. policy	Value incl. policy	Motivation
Gasoline powered internal combustion engine vehicle, Nissan Note Tekna 1.6l (ICEV)				
Lifetime	n_{ICEV}	5 y	Idem	Average lifetime of a company car in Belgium
Unit cost	UC_{ICEV}	13,953 € for 0 < vehicles < 5 13,787 € for 5 < vehicles < 50 13,455 € for >50 vehicles	Idem Idem Idem	Unit cost (Nissan 2013a); quantity reductions according to two Belgian Nissan distributors
Annual price evolution	$\dot{P}_{ICEV}$	−1.45%/y	Idem	Geometric mean 2005−2011 (European Union 2005−2011)
Fuel use	$Fuse_{ICEV}$	6.8l/100 km	Idem	(Nissan 2013c)
Gasoline price	P_{gasol}	0.7428 €/l	1.33 €/l	(Belgische Petroleum Federatie 2013)
Annual evolution gasoline price	$\dot{P}_{gasol}$	4%/y	Idem	(Belgische Petroleum Federatie 2013)
Maintenance cost	MC_{ICEV}	888 €/vehicles/y	Idem	Two Belgian Nissan distributors
Vehicle registration tax	T_{oICEV}	0 €	123 €	(FOD Financiën 2013b)
Price evolution registration tax	$\dot{P}_{ToICEV}$	0%/y	Idem	Geometric 2005−2012 (FOD Financiën 2013a)
Annual traffic tax	T_{nICEV}	0 €/y	263.87 €	(FOD Financiën 2013b)
Price evolution traffic tax	$\dot{P}_{TnICEV}$	0%/y	2.31%	Geometric mean 2005−2012 (FOD Financiën 2013a)
Investment deduction	$ID\%_{ICEV}$	0%	70%	(Belgisch Staatsblad 2009)
Investment deduction gasoline fuel	$ID\%_{fuel}$	0%	75%	(Belgisch Staatsblad 2009)

(*continued*)

Table 2. (*continued*)

Parameter	Symbol	Value excl. policy	Value incl. policy	Motivation
Solar-powered battery electric vehicle, Nissan LEAF (solar BEV)				
Lifetime	n_{BEV}	5 y	Idem	Average lifetime of a company car in Belgium
Unit cost	UC_{solBEV}	33,476 – 36,276 € for 0 < vehicles < 5 32,712 – 35,512 € for 5 < vehicles < 50 32,100 – 34,900 € for >50 vehicles	Max 36,606 € Max. 35,842 € Max. 35,230 €	In function of PV size; Unit cost (Nissan 2013a); quantity reductions according to two Belgian Nissan distributors; cost PV according to four Belgian companies
Annual price evolution	$\dot{P}_{BEV}$	−5.39%/y	Idem	(Weiss et al. 2012; EU Coalition−McKinsey 2010)
Fuel use	$Fuse_{BEV}$	0.173 kWh/km	Idem	(Nissan 2013b)
Solar power	$Psol_{BEV}$	3.29 kWp	Idem	Solar power needed to power the BEV over lifetime
Tradable green certificates	TGC	0€/kWh	0.093 €/kWh	(Flemish Energy Agency 2013)
Lifetime tradable green certificates	n_{TGC}	0 y	10 y	(Flemish Energy Agency 2013)
Maintenance cost	MC_{solBEV}	318.55 €/vehicles/y	Idem	Two Belgian Nissan distributors and 4 Belgian PV companies
Vehicle registration tax	T_{oBEV}	0 €	Idem	(FOD Financiën 2013b)
Price evolution registration tax	$\dot{P}_{ToBEV}$	0%/y	Idem	Geometric from 2005 till 2012 (FOD Financiën 2013a)
Annual traffic tax	T_{nBEV}	0€/y	75.77 €/y	(FOD Financiën 2013b)
Price evolution traffic tax	$\dot{P}_{TnBEV}$	0%/y	2.31%/y	Geometric mean 2005−2012 (FOD Financiën 2013a)
Investment deduction	$ID\%_{BEV}$	0%	120%	(Belgisch Staatsblad 2009)

4 times within the longer 20 year lifetime of the PV installation in years $t = 0, 5, 10, 15$.

$$z = \frac{n_{T_l}}{n_{T_s}} \quad \text{with} \quad n_{T_l} > n_{T_s} \tag{1}$$

$$\mathrm{UC}_{T_s} = \sum_{t=0^* n_{T_s}}^{(z-1)^* n_{T_s}} \left[\frac{\mathrm{UC}_{T_s}{}^* (1 + \dot{P}_{T_s})^t}{(1+r)^t} \right] \tag{2}$$

Life cycle cost data (including the initial required investment and operation and maintenance costs over the technologies' lifetime) is summarised in the coefficient c^1_{ijk}. We also calculate the optimal solutions when considering exclusively the initial investment, for example, due to bounded rationality. Data regarding the required investment are summarised in $c^{1'}_{ijk}$. The coefficients are calculated according to Equations (3a) to (7b). We consider the time value of money by discounting at discount rate r. Hence, in both the fully rational and the bounded-rational case, a net present value approach is used to calculate costs. The meaning and values of the symbols (including and excluding the impact of policy) are listed in Table 2. The cost of grid electricity is computed in Equations (3a) and (3b), considering an annual increase of the electricity price $\dot{P}_{\mathrm{electr}}$. The costs of solar PV comprise the initial investment minus the elevated investment deduction (Equation (4a)), and operating costs of maintenance and insurance minus the tradable green certificates (Equation (4b)). Note that the latter are obtained over a period of 10 years, rather than over the whole lifetime of 20 years of the installation. To satisfy the average demand of 150,000 kWh/y exclusively with PV, an installation with a capacity of 190.47 kWp (P_{tot}) would be required. Initial investment of the vehicles is calculated in Equations (5a), (6a) and (7a) according to the procedure explained in Equations (1) and (2) above. Note that tax benefits in the form of investment deductions are deducted from the initial unit cost. Operating costs of the ICVEs include fuel costs of gasoline, maintenance costs, registration and traffic taxes minus the tax benefits obtained (Equation (5b)). Operating costs of the grid powered BEVs are calculated simultaneously in Equation (6b), yet they include fuel costs of electricity rather than gasoline. Solar-powered BEVs imply no fuel costs over the lifetime of the vehicle, fuel costs of solar electricity are reflected in a higher initial purchase price. Solar-powered vehicles have the additional advantage of obtaining tradable green certificates (Equation (7b)). Numerical values of the coefficients in each interval k are presented in the upper part of Table 3 (in euros).

$$c^{1'}_{101} = \mathrm{UC}_{\mathrm{electr}} \tag{3a}$$

$$c^1_{101} = c^{1'}_{101} + \sum_{t=1}^{n} \frac{d_E{}^* P_{\mathrm{electr}}{}^* (1 + \dot{P}_{\mathrm{electr}})^t}{(1+r)^t} \tag{3b}$$

$$c^{1'}_{11k} = P_{\mathrm{tot}}{}^* \mathrm{UC}_{\mathrm{PV}(k)}{}^* (1 - \mathrm{EID}_{\%}) \tag{4a}$$

$$c^1_{11k} = c^{1'}_{11k} + \sum_{t=1}^{n} \frac{P_{\mathrm{tot}}{}^* (\mathrm{MC}_{\mathrm{PV},t} + \mathrm{INSC}_{\mathrm{PV},t}{}^* \mathrm{UC}_{\mathrm{PV}})}{(1+r)^t} - \sum_{t=1}^{n_{\mathrm{TGC}}} \frac{\beta^* P_{\mathrm{tot}}{}^* (1 - \alpha^* t)^* \mathrm{TGC}}{(1+r)^t} \tag{4b}$$

$$c^{1'}_{20k} = \sum_{t=0,5,10,15} \left[\frac{\mathrm{UC}_{\mathrm{ICEV}(k)}{}^* (1 + \dot{P}_{\mathrm{ICEV}})^{t^*} (1 - \mathrm{ID}_{\%\mathrm{ICEV}}{}^* t_r)}{(1+r)^t} \right] \tag{5a}$$

$$c^{1}_{20k} = c^{1'}_{20k} + \sum_{t=1}^{n} \frac{d_T * F_{\mathrm{use}_{\mathrm{ICEV}}} * P_{\mathrm{gasol}} * (1+\dot{P}_{\mathrm{gasol}})^{t*} (1-\mathrm{ID}_{\%\mathrm{fuel}} * t_r) + V * (1-\mathrm{ID}_{\%\mathrm{ICEV}} * t_r) * [\mathrm{MC}_{\mathrm{ICEV}} + T_{0_{\mathrm{ICEV}}} * (1+\dot{P}_{T_{0_{\mathrm{ICEV}}}})^{t} + T_{n_{\mathrm{ICEV}}} * (1+\dot{P}_{T_{n_{\mathrm{ICEV}}}})^{t}]}{(1+r)^{t}} \tag{5b}$$

$$c^{1'}_{21k} = \sum_{t=0,5,10,15} \left[\frac{\mathrm{UC}_{\mathrm{grBEV}(k)} * (1+\dot{P}_{\mathrm{BEV}})^{t*} (1-\mathrm{ID}_{\%\mathrm{BEV}} * t_r)}{(1+r)^{t}} \right] \tag{6a}$$

$$c^{1}_{21k} = c^{1'}_{21k} + \sum_{t=1}^{n} \frac{d_T * F_{\mathrm{use}_{\mathrm{BEV}}} * P_{\mathrm{electr}} * (1+\dot{P}_{\mathrm{electr}})^{t} * (1-\mathrm{ID}_{\%\mathrm{fuel}} * t_r) + V * (1-\mathrm{ID}_{\%\mathrm{BEV}} * t_r) * [\mathrm{MC}_{\mathrm{grBEV}} + T_{0_{\mathrm{BEV}}} * (1+\dot{P}_{T_{0_{\mathrm{BEV}}}})^{t} + T_{n_{\mathrm{BEV}}} * (1+\dot{P}_{T_{n_{\mathrm{BEV}}}})^{t}]}{(1+r)^{t}} \tag{6b}$$

$$c^{1'}_{22k} = \sum_{t=0,5,10,15} \left[\frac{\mathrm{UC}_{\mathrm{solBEV}(k)} * (1+\dot{P}_{\mathrm{BEV}})^{t*} (1-\mathrm{ID}\ _{\%\mathrm{BEV}} * t_r)}{(1+r)^{t}} \right] \tag{7a}$$

$$c^{1}_{22k} = c^{1'}_{22k} + \sum_{t=1}^{n} \frac{V * (1-\mathrm{ID}_{\%\mathrm{BEV}} * t_r) * [\mathrm{MC}_{\mathrm{solBEV}} + T_{0_{\mathrm{BEV}}} * (1+\dot{P}_{T_{0_{\mathrm{BEV}}}})^{t} + T_{n_{\mathrm{BEV}}} * (1+\dot{P}_{T_{n_{\mathrm{BEV}}}})^{t}]}{(1+r)^{t}} - \sum_{t=1}^{n_{\mathrm{TGC}}} \frac{\beta * P_{\mathrm{solBEV}} * (1-\alpha * t) * \mathrm{TGC}}{(1+r)^{t}}. \tag{7b}$$

Hence, the economic objective function is as follows:

$$\mathrm{Min} \sum_{i=1}^{m} \sum_{j=1}^{p} \sum_{k \in \text{interval } i} c^{1}_{ijk} x_{ijk} \quad \text{Economic objective function.}$$

To demonstrate the added value of incorporating economies of scale using mixed integer programming in a MOMILP rather than simply assuming one cost interval for each technology in a MOLP, we compare the results of both approaches. Hence, in the MOLP we assume an 'average' cost interval for all technologies. In particular, the grid electricity only has one interval ($k = 1$), we assume solar PV to be in the fourth cost interval ($k = 4$), and all the vehicles are assumed to be in the second cost interval ($k = 2$). The according cost coefficients are listed in the lower part of Table 3.

4.1.2.2. Environmental objective function. The environmental impacts of the technologies are determined by means of life cycle assessment (LCA). In our research, we use the LCA model described by De Schepper et al. (2014). Moreover, we conduct an attributional LCA, which serves to assess the environmentally physical flows of a past, current or future product system. Hence, we make use of average values for current technologies, as available in the EcoInvent database. It may be argued that a consequential approach may be the more appropriate choice for this study, since this research attempts to support future decision-making. However, a consequential LCA requires detailed data on marginal changes in the technological system as a consequence of a choice for a certain product. In this light, one may wonder about the marginal emission factor at the exact moment of charging the electric vehicles and of using the solar electricity. As many of this required data is either unavailable or very uncertain, the authors have opted to use an attributional LCA model in this study. The applied LCA methodology complies to the relevant ISO standards (14040-14044:2006). Unit processes are selected from the EcoInvent database, based on the best available match with the real projections at hand. The different scenarios are assessed for their impact on climate change on a 100 year time

Table 3. Numerical values of the economic LCC (€) and environmental LCE (ton CO_2-eq) coefficients in the MOMILP and the MOLP model.

			Including policy			Excluding policy		
Technology (i)	Type (j)	Interval (k)	Economic coefficient LCC(c^1_{ijk})	Economic coefficient IC ($c^{1'}_{ijk}$)	Environmental coefficient LCE (c^2_{ijk})	Economic coefficient LCC (c^1_{ijk})	Economic coefficient IC ($c^{1'}_{ijk}$)	Environmental coefficient LCE (c^2_{ijk})
Multi-objective mixed integer linear programming (MOMILP)								
$i=1$	$j=0$	$k=1$	224,592.31	0.00	1,089.00	220,079.66	0	1089.00
$i=1$	$j=1$	$k=1$	269,593.89	346,036.63	191.10	450,785.26	409,510.81	191.10
$i=1$	$j=1$	$k=2$	286,303.98	362,131.36	191.10	450,785.26	409,510.81	191.10
$i=1$	$j=1$	$k=3$	261,268.84	337,989.27	191.10	440,964.07	399,987.30	191.10
$i=1$	$j=1$	$k=4$	227,888.66	305,799.82	191.10	401,679.31	361,893.27	191.10
$i=1$	$j=1$	$k=5$	177,818.37	257,515.63	191.10	342,752.16	304,752.23	191.10
$i=1$	$j=1$	$k=6$	144,438.18	225,326.18	191.10	303,467.40	266,658.20	191.10
$i=1$	$j=1$	$k=7$	127,748.09	209,231.45	191.10	283,825.02	247,611.19	191.10
$i=2$	$j=0$	$k=1$	495,097.43	237,668.85	909.53	524,958.18	311,872.73	909.53
$i=2$	$j=0$	$k=2$	492,268.02	234,839.44	909.53	521,245.32	308,159.87	909.53
$i=2$	$j=0$	$k=3$	486,609.24	229,180.66	909.53	513,819.84	300,734.39	909.53
$i=2$	$j=1$	$k=1$	357,822.42	311,584.33	332.76	585,633.37	526,218.21	332.76
$i=2$	$j=1$	$k=2$	349,665.76	303,427.67	332.76	571,858.02	512,442.86	332.76
$i=2$	$j=1$	$k=3$	343,140.44	296,902.34	332.76	560,837.75	501,422.59	332.76
$i=2$	$j=2$	$k=1$	390,013.07	366,928.81	182.08	610,526.40	581,562.70	182.08
$i=2$	$j=2$	$k=2$	381,856.41	358,772.16	182.08	596,751.05	567,787.35	182.08
$i=2$	$j=2$	$k=3$	375,331.08	352,246.83	182.08	585,730.78	556,767.07	182.08
Multi-objective linear programming (MOLP)								
$i=1$	$j=0$	$k=1$	224,592.31	0.00	1089.00	220,079.66	0	1089.00
$i=1$	$j=1$	$k=4$	227,888.66	305,799.82	191.10	401,679.31	361,893.27	191.10
$i=2$	$j=0$	$k=2$	492,268.02	234,839.44	909.53	521,245.32	308,159.87	909.53
$i=2$	$j=1$	$k=2$	349,665.76	303,427.67	332.76	571,858.02	512,442.86	332.76
$i=2$	$j=2$	$k=2$	381,856.41	358,772.16	182.08	596,751.05	567,787.35	182.08

dimension (kg CO_2-eq) using the IPCC 2007 GWP 100a v1.02 single issue method[1]. Regarding the transportation technologies, we consider (1) the life cycle impact of the production and assembly of the vehicle, including the environmental impact of battery production (2) the well-to-tank impact, i.e. production and distribution of the energy carrier, and (3) the tank-to-wheel impact, i.e. conversion from energy carrier to transport. As regards the energy technologies, we take into account the GHG emissions of (1) the generation and (2) the distribution phase. Data regarding life cycle environmental emissions is represented by means of c_{ijk}^2 . The numerical value of the coefficients (in ton CO_2-eq) can be found in Table 3.

The environmental objective function is expressed the following way:

$$\text{Min} \sum_{i=1}^{m} \sum_{j=1}^{p} \sum_{k \in \text{interval } i} c_{ijk}^2 x_{ijk} \quad \text{Environmental objective function.}$$

4.1.3. Sensitivity analysis

To determine the sensitivity of the economic model coefficients, a Monte Carlo sensitivity analysis is conducted in which we vary the input data assuming a minimum (maximum) deviation of -10% ($+10\%$) of the assumed parameter values in Table 2. Results are presented in Table 4. The first three lines indicate the base case, the minimum and the maximum value obtained after varying all the input parameters. The last three lines give the sensitivity with respect to the three most influencing model parameters. Note that a positive (negative) sign indicates that the LCC will increase (decrease) with an increase of the respective parameter. The absolute value indicates the percentage of the spread in the life cycle cost that is due to a variation of $\pm 10\%$ of the assumed parameter value. The most important parameter to determine the LCC of the grid electricity is the unit cost of electricity (UC_{electr}) to be paid by the company. We find three parameters with a large influence on the LCC of solar PV, i.e. the amount of solar radiation (β), the unit cost of the installation (UC_{PV}), and the tradable green certificates (TGC). The LCC of the ICVEs is largely determined by the unit cost of the vehicles (UC_{ICEV}), the fuel use of the vehicles ($\text{Fuse}_{\text{ICEV}}$), and the gasoline price (P_{gasol}). We find two parameters that are large influencers of the LCC of the BEVs, being the unit cost (UC_{BEV}) and the investment deduction of the vehicles ($\text{ID}\%_{\text{BEV}}$). Hence, for both the energy technologies and the vehicles, the initial purchase price is a large influencer of the total life cycle costs.

4.1.4. Constraints

Following the model from Section 2, we can establish the link between (1) grid electricity and grid powered BEVs and (2) solar PV electricity and solar-powered BEVs as follows:

$$\sum_{k \in \text{Interval}_{1,0}} x_{10k} = x_{10} + e_{\text{grid}} x_{21} \quad \text{Relation grid electricity} - \text{grid BEV}$$

$$\sum_{k \in \text{Interval}_{1,1}} x_{11k} = x_{11} + e_{PV} x_{22} \quad \text{Relation PV electricity} - \text{solar BEV.}$$

Table 4. Monte Carlo sensitivity analysis of the economic life cycle cost LCC model coefficients (in €).

	LCC grid (c^1_{101})		LCC PV (c^1_{114})		LCC ICEV (c^1_{202})		LCC grBEV (c^1_{212})		LCC solBEV (c^1_{222})	
Base case	224,592.31		227,888.66		492,268.02		349,665.76		381,856.41	
Minimum	194,872.07		156,510.60		429,635.56		291,749.67		337,897.67	
Maximum	256,920.39		303,820.35		549,818.08		400,684.59		452,237.50	
Sensitivity with respect to…	UC_{electr}	87.2%	β	−50.5%	UC_{ICEV}	43.4%	UC_{grBEV}	62.0%	UC_{solBEV}	65.2%
	r	−11.0%	UC_{PV}	42.2%	$Fuse_{ICEV}$	19.3%	$ID\%_{BEV}$	−32.9%	$ID\%_{BEV}$	−29.3%
	$\dot{P}_{electr}$	1.8%	TGC	−5.4%	P_{gasol}	19.2%	$\dot{P}_{ToBEV}$	4.2%	$\dot{P}_{ToBEV}$	4.3%

The existence of economies of scale for vehicles implies the following constraint:

$$\sum_{k\in \text{Interval}_{2,j}} x_{2jk} = x_{2j} \;\; \forall j = 0, \ldots, 2 \quad \text{Economies of scale for vehicles.}$$

Considering economies of scale, intervals for the according technologies are established as follows:

$$\sum_{k\in \text{Interval}_{i,j}} y_{ijk} = 1 \quad \text{Exactly 1 interval active for technology } i,j$$

$$lb_{ijk}y_{ijk} \leq x_{ijk} \leq ub_{ijk}y_{ijk} \; \forall i,j;\; k \in \text{Interval}_{ij} \quad \text{Interval bounds for technology } i,j.$$

Finally, due to normalisation, we express the demand constraints the following way:

$$x_{10} + x_{11} = 1 \quad \text{Electricity demand}$$
$$x_{20} + x_{21} + x_{22} = 1 \quad \text{Transportation demand}$$

4.2. Results and discussion

We start with a discussion of the results that are obtained using MOMILP. Figures 3 and 4 respectively show the Pareto frontier when minimising the total economic life cycle cost (including the initial investment) and when minimising solely the initial investment, while satisfying the constraints on electricity and transportation demand. The according numerical values of the optimal solutions can be found in the upper part of Tables 5 and 6,

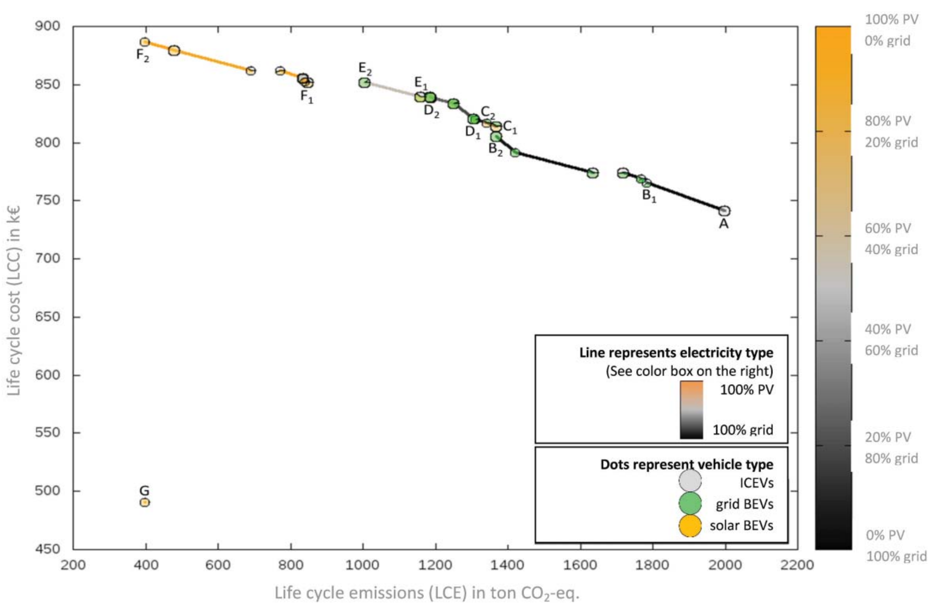

Figure 3. Pareto optimal solutions when simultaneously minimising life cycle emissions (LCE) and life cycle cost (LCC). Upper right: excluding policy impact. Bottom left: including policy impact.

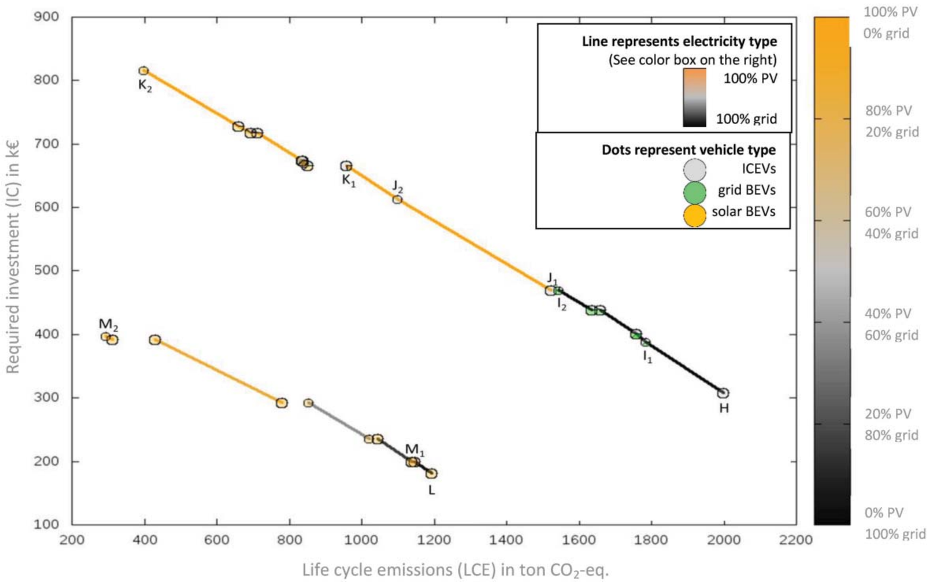

Figure 4. Pareto optimal solutions when simultaneously minimising life cycle emissions (LCE) and required investment (IC). Upper right: excluding policy impact. Bottom left: including policy impact.

i.e. the life cycle costs (LCC) and the required investment (IC) in *k*€, the life cycle emissions (LCE) in ton CO_2-eq. The percentage change compared to the economic lexicographic optima (%ΔLCC, %ΔIC, %ΔLCE), the proportion of electricity demand to be supplied by the grid (%grid) and by solar photovoltaics (%PV), and the proportion of transportation demand to be met by internal combustion engine vehicles (%ICEV), by grid powered battery electric vehicles (%gridBEV) and by solar-powered battery electric vehicles (%solarBEV). A distinction is made between the optimal solutions for the SME including policy measures and the optima excluding the impact of policy. Assuming rational decisions based on the full life cycle cost (LCC) and assuming the impact of current policy (Figure 3 bottom left), there is only one optimal solution (G) for the SME: the current electricity demand is fulfilled completely by means of solar PV, and transportation demand is met for 100% with solar BEVs. This solution is optimal from economic and environmental perspective. However, when the impact of policy is excluded (Figure 3 upper right), we see clearly that the use of environmentally beneficial technologies implies a trade-off with the economic performance. When solely optimising the economic objective (independently of the environmental objective), we find the economic lexicographic optimum; solution A. Here, demands are met entirely with grid electricity and ICEVs. When tolerating a slight increase of the LCC with 3.21%−8.69%, the ICEVs can be gradually replaced by grid powered BEVs, implying an emission decrease with 10.68%−31.56%, respectively (B_1-B_2). If the LCC is allowed to increase with 10.62%−13.26%, the grid BEVs will be partially accompanied with solar PV electricity, leading to emission reductions up to 40.65% (D_1-D_2). With a further increase of the LCC (14.95%−19.63%), solar panels can be used to satisfy electricity demands and solar BEVs are used for transport, leading to a maximal reduction of emissions of 80% (F_1-F_2).

If, due to bounded rationality, the SME would base its decision on the initial investment rather than on the full life cycle cost, there are plural optimal solutions (Table 6, Figure 4). If we exclude policy measures, we note that the lexicographic optima H and K_2 respectively correspond to the previously discussed lexicographic optima A and F_2. However, a large increase in required investment (26.18%−52.41%) has to be tolerated to decrease emissions by means of grid powered electric vehicles. Moreover, the grid BEVs will serve to meet no more than 78.68% of transportation demand (I_1−I_2). With a further increase of the initial investment (52.41%−98.89%), solar PV electricity is used in combination with ICEVs (J_1−J_2). Only if the required investment is allowed to increase with more than 116%, solar BEVs are used in combination with solar PV electricity (K_1−K_2). If the impact of policy is included, transportation needs are met completely with solar BEVs (L, M_1−M_2). The uptake of solar PV panels to meet electricity demand however implies an increase in the required investment of maximally 119.36%, allowing an emission reduction of 75.25% (M_1−M_2). Hence, policy measures do not necessarily push bounded-rational investors towards the environmental optimum.

In the introduction, we discussed the need of incorporating economies of scale into the analysis, an inherent discrete phenomenon that implies the use of mixed integer programming. If on the contrary we would assume an average cost interval for all technologies, we could solve the problem using MOLP. Compared to mixed integer programming, this has the advantage of being easier to solve, both in terms of computation times and complexity. For purposes of comparison we have included the optimal solutions using MOLP in our analysis. Results are presented in Figure 5, numerical values of the solutions can be found in the lower part of Tables 5 and 6. This clearly shows the interest of taking economies of scale (using MOMILP) into account. We see that MOLP can give either optimistic or pessimistic results compared to the MOMILP, the latter being much more accurate. Moreover, while we can conclude from the MOMILP analysis that policy measures effectively push rational investors towards one solution (solution G) that is optimal from economic and environmental viewpoint, the MOLP erroneously indicates that the use of grid electricity and grid BEVs (solution *e*) is also part of the efficient solution set. One could argue that it all depends on the value of the 'average' coefficients chosen, but in reality this is not the main point of focus. Due to the fact that MOLPs have continuous and strictly convex solution sets, they cannot provide efficient solution sets that accurately follow the non-continuous solution sets of MOMILPs. Moreover, as we provide more and more realistic input data into the MOMILP, it is clear that this will provide us more precise solution sets.

In this research, we limit ourselves to optimising the use of PV solar panels, electricity from the grid, ICEVs, grid BEVs, and solar BEVs. Note that other alternative technologies such as micro-wind, hydrogen vehicles, fuel cell vehicles, etc. might be more cost-efficient to decrease emissions. When dealing with energy systems, an important aspect to consider is variability. This is of special importance when renewable energy sources such as solar PV are employed. In this research, however, we focus on economic costs and environmental emissions of grid-connected systems rather than on technical aspects. Hence, we assumed a simplified average annual demand and supply of electricity. Moreover, we do not foresee storage of the PV electricity in a separate battery, nor do we consider backup systems on cloudy days. Inclusion of daily or hourly electricity demand and supply data (considering peak versus off-peak periods) and consideration of grid-to-vehicle and vehicle-to-grid concepts (Loisel, Pasaoglu, and Thiel 2014) are interesting topics for further research. This would require a third objective in our MOO model, which is an interesting topic for further investigation. We point to the fact that the environmental

Table 5. Pareto optimal solutions when minimising life cycle costs LCC (in k€) and life cycle emissions LCE (in ton CO_2-eq).

Solution	LCC	$\%\Delta LCC_A$	LCE	$\%\Delta LCE_A$	%grid	%PV	%ICEV	%gridBEV	%solarBEV
Multi-objective mixed integer linear programming (MOMILP)									
Excluding policy measures									
A	741.33		1998.53		100.00%	0.00%	100.00%	0.00%	0.00%
B_1	765.15	3.21%	1785.13	−10.68%	100.00%	0.00%	63.00%	37.00%	0.00%
	769.11	3.75%	1769.71	−11.45%	97.63%	2.37%	63.00%	37.00%	0.00%
	769.11	3.75%	1769.71	−11.45%	100.00%	0.00%	39.67%	60.33%	0.00%
	774.59	4.49%	1717.66	−14.05%	100.00%	0.00%	51.30%	48.70%	0.00%
	774.59	4.49%	1635.16	−18.18%	100.00%	0.00%	37.00%	63.00%	0.00%
	791.94	6.83%	1421.76	−28.86%	100.00%	0.00%	0.00%	100.00%	0.00%
B_2	805.78	8.69%	1367.89	−31.56%	94.00%	6.00%	0.00%	100.00%	0.00%
C_1	814.58	9.88%	1367.89	−31.56%	100.00%	0.00%	4.23%	32.77%	63.00%
C_2	817.15	10.23%	1343.49	−32.78%	100.00%	0.00%	0.00%	37.00%	63.00%
D_1	820.06	10.62%	1312.30	−34.34%	93.19%	6.81%	0.00%	100.00%	0.00%
	820.06	10.62%	1312.30	−34.34%	87.00%	13.00%	9.64%	90.36%	0.00%
	820.65	10.70%	1305.03	−34.70%	87.00%	13.00%	0.00%	100.00%	0.00%
	834.11	12.52%	1250.33	−37.44%	80.09%	19.91%	0.00%	100.00%	0.00%
	834.11	12.52%	1250.33	−37.44%	74.00%	26.00%	6.53%	93.47%	0.00%
	839.15	13.20%	1188.31	−40.54%	74.00%	26.00%	0.00%	100.00%	0.00%
D_2	839.60	13.26%	1186.09	−40.65%	73.75%	26.25%	0.00%	100.00%	0.00%
E_1	839.60	13.26%	1159.28	−41.99%	55.72%	44.28%	37.00%	0.00%	63.00%
	839.60	13.26%	1159.28	−41.99%	47.00%	53.00%	37.00%	63.00%	0.00%
E_2	852.15	14.95%	1004.96	−49.72%	47.00%	53.00%	10.24%	89.76%	0.00%
F_1	852.15	14.95%	847.31	−57.60%	0.00%	100.00%	63.86%	0.00%	36.14%
	852.81	15.04%	841.26	−57.91%	0.00%	100.00%	63.00%	0.00%	37.00%
	855.65	15.42%	836.56	−58.14%	0.26%	99.74%	62.00%	0.00%	38.00%
	855.65	15.42%	836.56	−58.14%	0.00%	100.00%	62.00%	1.86%	36.14%
	855.87	15.45%	834.25	−58.26%	0.00%	100.00%	62.00%	0.00%	38.00%
	862.14	16.30%	773.33	−61.31%	0.00%	100.00%	53.31%	0.00%	46.69%
	862.14	16.30%	692.37	−65.36%	3.72%	96.28%	37.00%	0.00%	63.00%
	879.50	18.64%	478.97	−76.03%	8.84%	91.16%	0.00%	0.00%	100.00%
F_2	886.86	19.63%	399.62	−80.00%	0.00%	100.00%	0.00%	0.00%	100.00%
Including policy measures									
G	490.94		399.62		0.00%	100.00%	0.00%	0.00%	100.00%
Multi-objective linear programming (MOLP)									
Excluding policy measures									
a	741.32		1998.53		0.00%	100.00%	0.00%	0.00%	100.00%
b	791.94	6.83%	1421.76	−28.86%	100%	0%	0%	100%	0%
c	816.83	10.19%	1271.09	−36.40%	100%	0%	0%	0%	100%
d	998.43	34.68%	373.33	−81.32%	0%	100%	0%	0%	100%
Including policy measures									
e	574.26		1421.76		100%	0%	0%	100%	0%
f	577.55	0.57%	523.09	−63.21%	0%	100%	0%	100%	0%
g	609.74	6.18%	373.33	−73.74%	0%	100%	0%	0%	100%

Table 6. Pareto optimal solutions when minimising required investment IC (in k€) and life cycle emissions LCE (in ton CO_2-eq).

Solution	IC	$\%\Delta IC_H$	LCE	$\%\Delta LCE_H$	%grid	%PV	%ICEV	%gridBEV	%solarBEV
Multi-objective mixed integer linear programming (MOMILP)									
Excluding policy measures									
$H\,(=A)$	308.16	0.00%	1998.53	0.00%	100.00%	0.00%	100.00%	0.00%	0.00%
I_1	388.84	26.18%	1785.13	−10.68%	100.00%	0.00%	63.00%	37.00%	0.00%
	401.48	30.28%	1757.43	−12.06%	97.08%	2.92%	63.00%	37.00%	0.00%
	401.48	30.28%	1757.43	−12.06%	100.00%	0.00%	41.80%	58.20%	0.00%
	438.23	42.21%	1658.52	−17.01%	100.00%	0.00%	38.57%	61.43%	0.00%
	438.23	42.21%	1635.16	−18.18%	100.00%	0.00%	37.00%	63.00%	0.00%
I_2	469.68	52.41%	1544.74	−22.71%	100.00%	0.00%	21.32%	78.68%	0.00%
J_1	469.68	52.41%	1522.64	−23.81%	47.00%	53.00%	100.00%	0.00%	0.00%
J_2	612.91	98.89%	1100.63	−44.93%	0.00%	100.00%	100.00%	0.00%	0.00%
K_1	666.03	116.13%	957.88	−52.07%	0.00%	100.00%	79.63%	0.00%	20.37%
	666.03	116.13%	850.38	−57.45%	0.00%	100.00%	64.29%	0.00%	35.71%
	669.31	117.20%	841.37	−57.90%	0.00%	100.00%	63.00%	0.00%	37.00%
	673.32	118.50%	837.20	−58.11%	0.00%	100.00%	62.00%	2.29%	35.71%
	674.17	118.77%	834.37	−58.25%	0.00%	100.00%	62.00%	0.00%	38.00%
	718.22	133.07%	711.71	−64.39%	0.00%	100.00%	44.50%	0.00%	55.50%
	718.22	133.07%	693.49	−65.30%	3.82%	96.18%	37.00%	0.00%	63.00%
	728.41	136.37%	659.19	−67.02%	0.00%	100.00%	37.00%	0.00%	63.00%
$K_2\,(=F_2)$	816.43	164.94%	399.62	−79.99%	0.00%	100.00%	0.00%	0.00%	100.00%
Including policy measures									
L	180.85		1193.26		100.00%	0.00%	0.00%	0.00%	100.00%
M_1	199.73	10.44%	1146.43	−3.92%	94.78%	5.22%	0.00%	0.00%	100.00%
	199.73	10.44%	1138.65	−4.58%	93.92%	6.08%	0.00%	0.00%	100.00%
	235.30	30.11%	1044.16	−12.50%	83.39%	16.61%	0.00%	0.00%	100.00%
	235.30	30.11%	1021.93	−14.36%	80.92%	19.08%	0.00%	0.00%	100.00%
	292.28	61.62%	854.63	−28.38%	62.29%	37.71%	0.00%	0.00%	100.00%
	292.28	61.62%	779.49	−34.68%	53.92%	46.08%	0.00%	0.00%	100.00%
	392.39	116.97%	430.43	−63.93%	15.04%	84.96%	0.00%	0.00%	100.00%
	392.39	116.97%	312.59	−73.80%	1.92%	98.08%	0.00%	0.00%	100.00%
M_2	396.71	119.36%	295.36	−75.25%	0.00%	100.00%	0.00%	0.00%	100.00%
Multi-objective linear programming (MOLP)									
Excluding policy measures									
h	234.84		1998.53		100%	0%	100%	0%	0%
i	303.43	29.21%	1421.76	−28.86%	100%	0%	0%	100%	0%
j	609.23	159.42%	523.09	−73.83%	100%	0%	0%	0%	100%
k	664.57	182.99%	373.33	−81.32%	0%	100%	0%	0%	100%
Including policy measures									
l	308.16		1998.53		100%	0%	100%	0%	0%
m	512.44	66.29%	1421.76	−28.86%	100%	0%	0%	100%	0%
n	567.79	84.25%	1271.09	−36.40%	100%	0%	0%	0%	100%
o	929.68	201.69%	373.33	−81.32%	0%	100%	0%	0%	100%

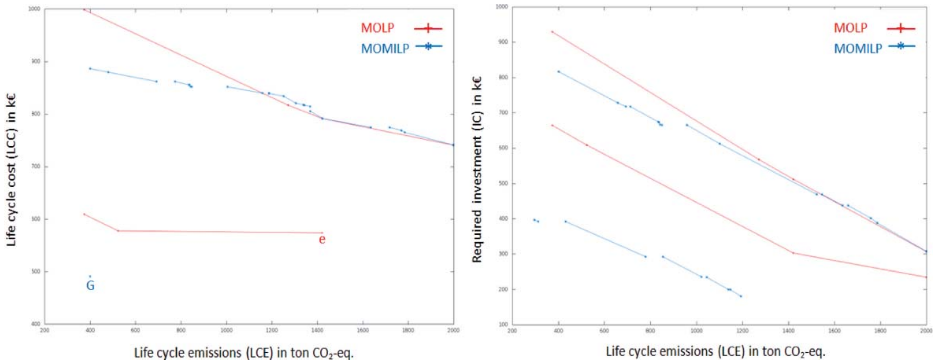

Figure 5. Pareto optimal solutions of multi-objective linear programming (MOLP) versus multi-objective mixed integer linear programming (MOMILP).

evaluation in this research focuses on the impact on climate change, i.e. the assessment of GHG emissions. This is in line with current European regulations regarding the 20−20−20 targets, in which targets are set to reduce GHG emissions with at least 20% by 2020 compared to 1990 levels (European Commission 2009). Nonetheless, other category impacts, such as ozone depletion, acidification, fossil fuel depletion, human toxicity, particulate matter formation, etc. are all relevant to the environmental assessment of clean technologies. This would require a multi-criteria approach that goes beyond the bi-objective model of this dissertation. Finally, we note that only the direct economic costs of the technologies are quantified. The use of BEVs however implies other inconveniences such as limited driving ranges and long charging times, two major barriers preventing the large uptake of this technology. The amount of BEVs in Belgium is scarce, with a total of 562 new electrified vehicles compared to 145,640 petrol vehicles in 2012 (FOD mobiliteit en transport - FEBIAC 2013). Hence, policy should continue stimulating technological development to overcome these practical drawbacks.

5. Conclusions and policy implications

This research proposes the use of MOO from economic and environmental viewpoint to find the optimal mixture of energy and transportation technologies, given required energy and transport demands. To obtain realistic results, economies of scale are taken into account. This inherently discrete phenomenon implies the use of mixed integer programming. While the use of continuous MOLP is easier to solve than MOMILP in terms of complexity and computation times, we demonstrate that MOLP is unable to provide the correct results that include the cost intervals or economies of scale for the different technologies. This paper applies the improved version of a developed algorithm to solve MOMILPs exactly (Vincent et al. 2013). A comparison is made between complete rationality − i.e. minimising economic life cycle costs − and bounded rationality − i.e. minimising solely the required investment. To distinguish between the optima with and without subsidies, the impact of policy measures on the Pareto frontier is assessed. The approach is illustrated with a Belgian SME that seeks to find the optimal combination of technologies to satisfy electricity and transportation demands, while minimising environmental emissions and economic costs. Technologies at hand are solar PV and grid electricity to cover electricity needs, and ICEVs, grid powered BEVs and solar-powered

BEVs to cover transportation requirements. The Pareto frontiers clearly illustrate a trade-off between economic and environmental performances. Results demonstrate that at the time of writing, electricity from solar panels is still more expensive than purchasing electricity from the grid in the absence of energy policies. Likewise, the use of BEVs is still more costly than the use of petrol fueled ICEVs. It is demonstrated that the impact of grid powered BEVs to reduce GHG emissions is limited, yet they are less costly than solar panels to decrease emissions. When BEVs are powered with electricity generated from solar panels rather than with electricity from the Belgian grid, the environmental performance is largely improved, albeit at a higher economic cost.

Using MOMILP, current policy is found to be targeting rational investors who consider full life cycle costs. Moreover, under the current policy rational investors are pushed towards one single environmental optimum, which implies the use of solar panels for electricity generation and the use of solar-powered BEVs for transportation. However, assuming that a bounded-rational investor solely takes into consideration the initial required investment (for instance a private investor who manages a budget for one year only), the environmental optimum is not necessarily achieved. It is therefore important that policy makers point to the importance of considering life cycle costs. To this end, they could match the financial support for a PV installation with the support needed to make that installation breakeven (rather than providing one single certificate price and elevated investment deduction percentage for all installations). One of the major drawbacks of the current Belgian policy to stimulate the uptake of BEVs relates to the subsidisation of the higher initial purchase price of the vehicles. Moreover, under current regulation, an investment deduction of 120% for the vehicles is granted. Whilst this represents a large financial incentive, we note that only companies (rather than individuals) can profit from this measure. Furthermore, besides the focus on the high purchase price of the vehicles, policy should stimulate technological development to overcome major drawbacks such as limited driving ranges and long charging times.

Acknowledgements

The authors would like to give special thanks to Audrey Cerqueus (University of Nantes) for the ongoing support and her constructive remarks regarding this submission.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

Sebastien Lizin thanks the Research Foundation Flanders (FWO) for funding his postdoctoral fellowship under Grant 12G5415N, allowing him to revise the manuscript.

Note

1. As the sectors of heat and electricity and transport are the two largest contributors to global greenhouse gas emissions (International Energy Agency 2012), we focus in our LCA model on CO_2-eq emissions. Other category impacts such as fossil depletion, human toxicity, particulate matter formation, etc. are also assessed in the LCA, yet they are beyond the scope of the bi-objective optimisation model. Results are available from the authors upon request.

References

Arnette, Andrew, and Christopher W. Zobel. 2012. "An Optimization Model For Regional Renewable Energy Development." *Renewable and Sustainable Energy Reviews* 16 (7): 4606−4615. http://dx.doi.org/10.1016/j.rser.2012.04.014.

Badcock, Jeremy, and Manfred Lenzen. 2010. "Subsidies for Electricity-Generating Technologies: A Review." *Energy Policy* 38 (9): 5038−5347. http://dx.doi.org/10.1016/j.enpol.2010.04.031.

Boardman, Anthony E., David H. Greenberg, Aidan R. Vining, and David L. Weimer. 2011. *Cost-Benefit Analysis: Concepts and Practice* Edited by Pearson. 4th ed. Upper Saddle River, NJ: Prentice Hall.

Belgisch Staatsblad. 2009 "Programmawet 23.12.2009." Accessed April 4, 2013. www.ejustice.fgov.be

Belgische Petroleum Federatie. 2013. "Maximumprijzen benzine". Accessed January 4, 2013. www.petrolfed.be

De Schepper, Ellen, Steven Van Passel, Sebastien Lizin, Wouter M.J. Achten, and Karel Van Acker. 2014. "Cost-efficient Emission Abatement of Energy and Transportation Technologies: Mitigation Costs and Policy Impacts for Belgium." *Clean Technologies and Environmental Policy* 16 (6): 1107−1118. doi:10.1007/s10098-014-0713-z.

Doucette Reed T., and Malcolm D. McCulloch. 2011. "Modeling the CO_2 Emissions from Battery Electric Vehicles Given the Power Generation Mixes of Different Countries." *Energy Policy* 39 (2): 803−811. doi:10.1016/j.enpol.2010.10.054.

European Commission. 2009. "Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC." 16−62. Brussels, (Belgium).

European Commission. 2012. "Commission Regulation (EU) No 601/2012 of 21 June 2012 on the monitoring and reporting of greenhouse gas emissions pursuant to Directive 2003/87/EC of the European Parliament and of the Council". 30−104. Brussels

EU Coalition - McKinsey. 2010. "A portfolio of power-trains for Europe: a fact-based analysis - The role of battery electric vehicles, plug-in hybrids and fuel cell electric vehicles." Brussels (Belgium).

Eurostat. 2012. "Electricity prices for industrial consumers." Accessed October 17, 2013. http://epp.eurostat.ec.europa.eu

Fattori, Fabrizio, Norma Anglani, and Giuseppe Muliere. 2014. "Combining Photovoltaic Energy With Electric Vehicles, Smart Charging and Vehicle-to-Grid." *Solar Energy* 110: 438−451. http://dx.doi.org/10.1016/j.solener.2014.09.034.

Flemish Energy Agency. 2013. "Groene stroomcertificaten voor fotovoltaïsche zonnepanelen." Accessed March 3, 2013. www.energiesparen.be

FOD Financiën. 1992. "Wetboek van de Inkomstenbelastingen." Brussels (Belgium).

FOD Financiën. 2013a. "Tarieven van de verkeersbelasting 2005-2012." Accessed April 4, 2013. http://koba.minfin.fgov.be

FOD Financiën. 2013b. "Tarieven van de verkeersbelasting 2012-2013." Accessed April 2, 2013. http://koba.minfin.fgov.be

FOD mobiliteit en transport - FEBIAC. 2013. "Inschrijvingen van nieuwe wagens per brandstofsoort." Accessed February 2, 2014. www.febiac.be

Gigerenzer, Gerd, and Reinhard Selten. 2002. *Bounded Rationality: The Adaptive Toolbox*. Cambridge, MA: MIT Press.

Hennings Wilfried, Stefan Mischinger, and Jochen Linssen. 2013. "Utilization of Excess Wind Power in Electric Vehicles." *Energy Policy* 62: 139−144. http://dx.doi.org/10.1016/j.enpol.2013.06.134.

International Energy Agency. 2012. "CO_2 emissions from fuel combustion." 1−125, Paris.

Kempton, Willett, and Steven Letendre. 1997. "Electric Vehicles as a New Power Source for Electric Utilities." *Transportation Research Part D: Transport and Environment* 2 (3): 157−175.

Liu, Pei, Efstratios N. Pistikopoulos, and Zheng Li. 2010. "An Energy Systems Engineering Approach to the Optimal Design of Energy Systems in Commercial Buildings." *Energy Policy* 38 (8): 4224−4231. http://dx.doi.org/10.1016/j.enpol.2010.03.051.

Liu, Wen, Weihao Hu, Henrik Lund, and Zhe Chen. 2013. "Electric Vehicles and Large-scale Integration of Wind Power – the Case of Inner Mongolia in China." *Applied Energy* 104: 445−456. http://dx.doi.org/10.1016/j.apenergy.2012.11.003.

Loisel, Rodica, Guzay Pasaoglu, and Christian Thiel. 2014. "Large-scale Deployment of Electric Vehicles in Germany by 2030: An Analysis of Grid-to-Vehicle and Vehicle-to-Grid Concepts." *Energy Policy* 65: 432−443. http://dx.doi.org/10.1016/j.enpol.2013.10.029.

Mavrotas, George, and Danae Diakoulaki. 1998. "A Branch and Bound Algorithm for Mixed Zero-One Multiple Objective Linear Programming." *European Journal of Operational Research* 107 (3): 530−541. http://dx.doi.org/10.1016/S0377-2217(97)00077-5.

Mavrotas, George, and Danae Diakoulaki Diakoulaki. 2005. "Multi-criteria Branch and Bound: A Vector Maximization Algorithm for Mixed 0-1 Multiple Objective Linear Programming." *Applied Mathematics and Computation* 171 (1): 53−71. http://dx.doi.org/10.1016/j.amc.2005.01.038.

Mavrotas George, Danae Diakoulaki, Kostas Florios, and Paraskevas Georgiou. 2008. "A Mathematical Programming Framework for Energy Planning in Services' Sector Buildings Under Uncertainty in Load Demand: The Case of a Hospital in Athens." *Energy Policy* 36 (7): 2415−2429. http://dx.doi.org/10.1016/j.enpol.2008.01.011.

Mwasilu, Francis, Jackson John Justo, Eun-Kyung Kim, Ton Duc Do, and Jin-Woo Jung. 2014. "Electric Vehicles and Smart Grid Interaction: A Review on Vehicle to Grid and Renewable Energy Sources Integration." *Renewable and Sustainable Energy Reviews* 34: 501−516. http://dx.doi.org/10.1016/j.rser.2014.03.031.

Nissan. 2013a. "Algemene prijslijst België." Accessed March 18, 2013. www.nissan.be

Nissan. 2013b. "Nissan Leaf." Accessed March 18, 2013. www.nissan.be

Nissan. 2013c. "Nissan Note". Accessed March 12, 2013. www.nissan.be

Pindyck, Robert S., and Daniel L. Rubinfeld. 2009. *Microeconomics*. 7th ed. Upper Saddle River, NJ: Prentice Hall.

Santos, Georgina, Hannah Behrendt, and Alexander Teytelboym. 2010. "Part II: Policy Instruments for Sustainable Road Transport." *Research in Transportation Economics* 28 (1): 46−91. http://dx.doi.org/10.1016/j.retrec.2010.03.002.

Sathaye J., and S. Meyers. 1995. *Greenhouse Gas Mitigation Assessment: A Guidebook*. Dordrecht: Kluwer Academic Publishers.

Šúri, Marcel, Thomas A. Huld, Ewan D. Dunlop, and Heinz A. Ossenbrink. 2007. "Potential of solar electricity generation in the European Union member states and candidate countries." *Solar Energy* 81 (10): 1295−1305. doi: http://dx.doi.org/10.1016/j.solener.2006.12.007.

Tulpule, Pinak J., Vincenzo Marano, Stephen Yurkovich, and Giorgio Rizzoni. 2013. "Economic and Environmental Impacts of a PV Powered Workplace Parking Garage Charging Station." *Applied Energy* 108: 323−332. http://dx.doi.org/10.1016/j.apenergy.2013.02.068.

Vincent, Thomas, Florian Seipp, Stefan Ruzika, Anthony Przybylski, and Xavier Gandibleux. 2013. "Multiple Objective Branch and Bound for Mixed 0-1 Linear Programming: Corrections and Improvements for the Biobjective Case." *Computers & Operations Research* 40 (1): 498−509. http://dx.doi.org/10.1016/j.cor.2012.08.003.

Wang, Jiang-Jiang, You-Yin Jing, Chun-Fa Zhang, and Jun-Hong Zhao. 2009. "Review on Multi-Criteria Decision Analysis Aid in Sustainable Energy Decision-Making." *Renewable & Sustainable Energy Reviews* 13 (9): 2263−2278. doi:10.1016/j.rser.2009.06.021.

Weiss, Martin, Martin K. Patel, Martin Junginger, Adolfo Perujo, Pierre Bonnel, and Geert van Grootveld. 2012. "On the electrification of road transport−Learning rates and price forecasts for hybrid-electric and battery-electric vehicles." *Energy Policy* 48: 374−393. doi: http://dx.doi.org/10.1016/j.enpol.2012.05.038.

Zhang, Qi, Tetsuo Tezuka, Keiichi N. Ishihara, and Benjamin C. McLellan. 2012. "Integration of PV Power Into Future Low-Carbon Smart Electricity Systems with EV and HP in Kansai Area, Japan" *Renewable Energy* 44: 99−108. doi:10.1016/j.renene.2012.01.003.