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# Evaluation of the Electromobility Potential Index and Results for 46 Major Cities

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**Abstract**

The Electromobility Potential Index (EMPI) is an innovative tool to evaluate the potential for the successful introduction of electric vehicles in large cities. Many local conditions affect the sustainability such as energy mix, climate and traffic flow. The existing EMPI has been fine-tuned to allow for a greater degree of precision and a more explicit evaluation, which will give a deeper insight of the potential and effects of the introduction of electric vehicles in the 46 cities considered. These results may help automakers and governments make the right decisions in order to realize sustainable solutions for individual mobility in megacities. This paper highlights the improvements for the EMPI and presents the results for the cities considered. Furthermore, the robustness of the evaluation is investigated by identifying the effects of varying the weighting factors and city parameters.

*Keywords: electric vehicles; megacity; sustainability; index*

## 1 Introduction

The Electromobility Potential Index (EMPI) is a tool to evaluate the potential for sustainable success of electric vehicles in cities [1]. The goal of the tool is to help both automakers and public authorities predict if the introduction of battery electric vehicles (BEV) would be successful and sustainable under the current local conditions, which take into consideration the ecological, economical, infrastructural and socio-demographical aspects.

## 2 Approach

While the first version of the EMPI presented in [1] already delivers reliable results, this paper will detail the modifications made and analyze the robustness of the index by carrying out a sensitivity analysis for the evaluating factors and the crucial input data.

## 3 Evaluation Criteria

### 3.1 Definition of the criteria

The EMPI evaluates the potential for the successful introduction of BEV in major cities with respect to “sustainability” (in both the environmental and economic sense), “user acceptance” and “readiness”. The five key performance indicators (KPI) that initially defined the EMPI in [1] are:

The *BEV Consumption* ($KPI_W$) evaluates the total energy consumption of a BEV under city-specific conditions.

The *Environmental Impact* ($KPI_E$) analyses the global balance of $CO_2$ emissions on a well-to-wheel basis between the usage of BEV and internal combustion engine vehicles (ICEV).

The *BEV Costs* ($KPI_C$) compares the total costs of ownership (TCO) for BEV and ICEV. Furthermore,

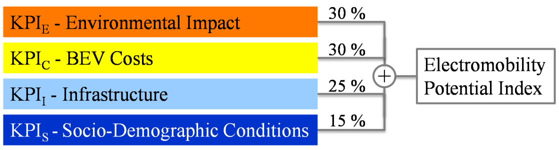


Figure 1: Key Performance Indicators of EMPI

it respects a city's wealth level measured in GDP per capita and appreciates any efforts done by the government to promote and boost the purchase and usage of BEV.

The *Infrastructure* indicator (*$KPI_I$*) evaluates the traffic conditions depending on the efficiency of public transport and road systems and the current efforts of a city for building up the necessary charging infrastructure for BEV.

The *Socio-Demographic Conditions* (*$KPI_S$*) include the local living conditions and the reliability of the government.

However, that initial evaluation has been reviewed by the authors and modified. In order to combine all input data as linearly independent as possible, *$KPI_W$* has been removed since its effects are already accounted for in *$KPI_C$* and *$KPI_I$*.

The modified composition of the EMPI with its four KPI, including the respective weightings, is shown in Fig. 1, while a simplified overview of the EMPI tool in Simulink is given in Fig. 2.

## 3.2 Weightings of the criteria

The EMPI gives a score for each evaluated city on a scale of 0 to 100. Cities exceeding the critical value of 50 show acceptable boundary conditions and therefore have the potential for a sustainable and successful introduction of BEV. Assigning appropriate weighting factors to an evaluation index such as the EMPI is at the same time both important and subjective. In literature, methods on how to define weighting factors can be found e.g. Analytical Hierarchy Process (AHP) [2] or PROMETHEE [3]. Because both approaches provide methods for decision making processes between several alternatives in order to serve a higher goal, they are not applicable when identifying the weighting factors for the EMPI, which is meant to be an evaluation and not necessarily a ranking index. Hence, the authors defined the weighting of the KPI to their best knowledge and belief.

The *Environmental Impact* (*$KPI_E$*) and the *BEV Costs* (*$KPI_C$*) are considered as the main success factors and are thus equally weighted with 30 % share each. A weighting of 25 % is given to the *Infrastructure* indicator (*$KPI_I$*) and 15 % for the *Socio-Demographic Conditions* (*$KPI_S$*).

The definitions of each of the four KPI as well as the weightings of the elements underneath are taken from the initial EMPI in [1].

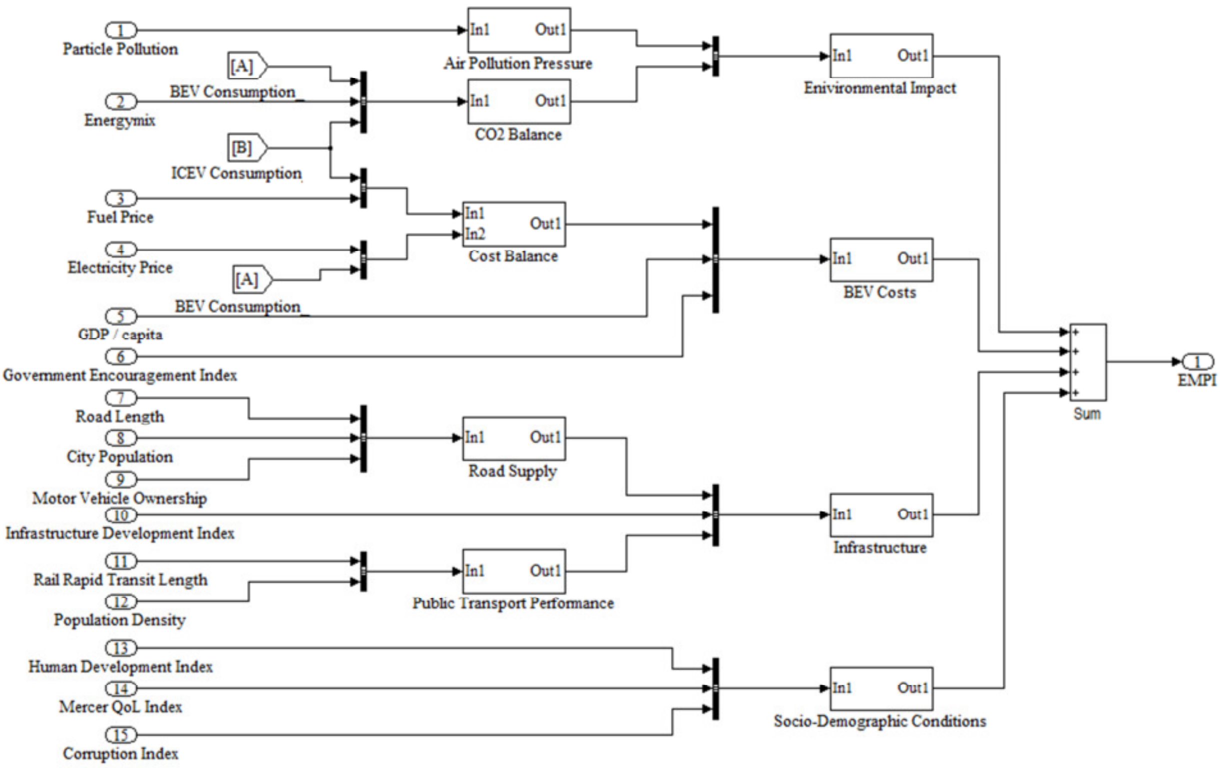


Figure 2: Simplified overview of the EMPI tool in Simulink

# 4 Modeling

## 4.1 Range

The initial EMPI is based on a reference BEV with a fixed range of 150 km in every considered city [1]. Due to local conditions the energy consumption may vary for each city, which results in different sizes and costs for the battery pack to fulfill the range requirement. Now, the authors take a step further and follow the approach of evaluating ideal BEV with ranges that suit the local requirements.

Determining appropriate range requirements is a very crucial point of a BEV concept, since the battery is a major cost factor. A conflicting fact, however, is the significant gap between customers' wishes and needs [4]. In this paper, the range requirements are defined by the latter.

Fleet tests are a very helpful method to determine the range requirements for different user groups under local conditions. Automakers and research institutions have done this before such as in [5-9]. However, fleet tests are cost-intensive and time-consuming and can only be applied in selected locations. Thus, a theoretical approach to determine the range requirements had to be developed. A promising way is to apply the theory of travel time budget (TTB). It was found that on average, humans spend a fixed period of their daily time travelling, which is approximately 1.1 h per person per day [10]. The authors prove the stability of this theorem over a wide range of income levels, geographical and cultural settings, but state as well that the $TTB_{\text{city}}$ in congested cities is higher (up to 30 %) than in rural areas:

$$TTB_{\text{city}} = 1.3\, TTB. \tag{1}$$

The average daily range requirement $R_{\emptyset}$ for a vehicle in a congested city can be stated as the product of $TTB_{\text{city}}$ and the local average driving speed $v_{\emptyset}$, assuming that the car is used by one person and as the only mode of transport:

$$R_{\emptyset} = TTB_{\text{city}} v_{\emptyset}. \tag{2}$$

Designing a car just for the average range requirements is not sufficient. Designing a BEV for the 100th percentile daily travel distances isn't advisable either due to the resulting costs and weight of the battery. The BEV used for the EMPI are considered acceptable if they are able to fulfill 95 % of all daily travels, assuming they will be charged overnight. The results of fleet trials done with MINI in Berlin [7] and in the UK [8] reveal that the 95th percentile of the daily travel distance with ICEV is related to the 50th percentile with nearly a factor of 2:

$$R_{95} = 2R_{\emptyset}. \tag{3}$$

Quantitatively, the approximate 95th percentile of the measured daily driving behavior in Berlin is 73 km [7] and 77 km in the UK [8]. While no speed data of the more rural UK areas are available to the authors, a measured average speed of $v_{\emptyset} = 24.2$ km/h was stated for Berlin [11]. Applying this in (3) leads to a calculated $R_{95} = 69.2$ km, which only slightly underestimates the real measured data (error < 10 %). Thus, the presented approach of estimating the required range is sufficiently appropriate for use in the EMPI.

Another factor that needs to be targeted is the range anxiety, which captures the drivers' concern of not reaching their destination when driving a BEV [12]. While [13] states that this phenomenon affects drivers as soon as the battery charge falls below 50 %, no literature is found that quantifies a sufficient amount of rest range a BEV should have at the end of a day for the driver to still feel comfortable. Here, a buffer of 15 km is considered, resulting in the required range:

$$R = R_{95} + 15\text{ km}. \tag{4}$$

Inserting (1), (2) and (3) in (4) leads to a linear relationship between $R$ and a city's average driving speed $v_{\emptyset}$:

$$R = 2.86 v_{\emptyset} + 15\text{ km}. \tag{5}$$

Applying the local traffic flows to (5), Table 1 shows the required ranges for 46 cities worldwide.

Table 1: Required BEV Range [km] (5) covering 95th percentile of all daily distances for 46 cities

| City | Range | City | Range |
|---|---|---|---|
| Johannesburg | 135 | Houston | 75 |
| Toronto | 135 | Atlanta | 75 |
| San Francisco | 107 | Melbourne | 75 |
| Munich | 107 | Shanghai | 72 |
| Paris | 104 | Buenos Aires | 72 |
| Moscow | 101 | Rio de Janeiro | 72 |
| Chongqing | 101 | Osaka-Kobe | 72 |
| Singapore | 97 | Guangzhou | 72 |
| Kuala Lumpur | 91 | Shenzhen | 72 |
| Bogota | 91 | Kolkata | 69 |
| Tokyo | 89 | London | 69 |
| Hong Kong | 87 | Beijing | 66 |
| Delhi | 87 | Chicago | 66 |
| New York City | 87 | Tehran | 66 |
| Sao Paolo | 87 | Mexico City | 64 |
| Wuhan | 87 | Karachi | 61 |
| Berlin | 84 | Istanbul | 59 |
| Seoul | 84 | Bangkok | 58 |
| Lima | 82 | Cairo | 52 |
| Lagos | 81 | Jakarta | 52 |
| Los Angeles | 79 | Manila | 51 |
| Washington | 79 | Ho Chi Minh City | 38 |
| Mumbai | 78 | Dhaka | 32 |

## 4.2 Energy Consumption

The energy consumptions for both BEV and ICEV are used for the comparisons under $KPI_E$ and $KPI_C$, see Fig. 2. In order to calculate the consumptions in a time-efficient manner, a so-called lumped-parameter simulation [14] is chosen and slightly modified to compensate for some known overestimations. This type of modeling is less complex and much easier to apply than time-step based simulations, but relatively accurate (error < 15%).

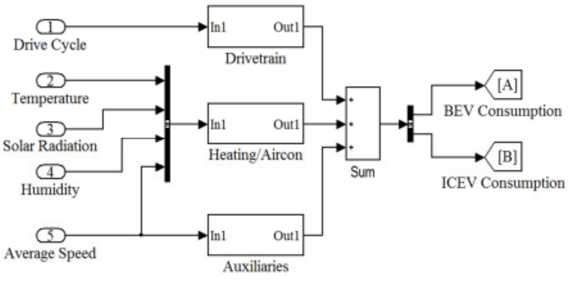


Figure 3: City parameters influencing the energy consumptions of ICEV and BEV

Table 2: Main specifications of the reference BEV/ICEV

| Description | Constants | Values |
|---|---|---|
| Curbweight ICEV | $m_{curb,ICEV}$ | 1100 kg |
| Baseweight BEV (excl. Battery and Drivetrain) | $m_{base,BEV}$ | 650 kg |
| Additional Weight (Driver) | $m_{add}$ | 75 kg |
| Frontal Area | A | 2.05 $m^2$ |
| Drag Coefficient | $c_d$ | 0.31 |
| Wheel Radius | $r_w$ | 0.29 m |
| Tyre Roll Resistance Factor | $f_r$ | 0.01 |
| Efficiency Drivetrain BEV | $\eta_{DT,BCEV}$ | 0.8 |
| Efficiency Drivetrain ICEV | $\eta_{DT,ICEV}$ | 0.16 … 0.24 |
| Energy Density Battery Cell (LiMn) | | 118 Wh/kg |
| Regenerative Braking Rate | | 55 % |
| Power Auxiliaries | $P_{aux}$ | 700 W |

One major improvement to the initial EMPI is the integration of a city specific vehicle. This allows the user to define the approximate dimensions and technical specifications of a reference vehicle. In an iterative process, the masses of battery and drivetrain are calculated on the basis of the range requirements from Table 1, taking into consideration approximately 50 % secondary mass effects. This calculation also takes into account city-specific characteristics such as drive cycles, which were modified from standard cycles to better meet the characteristics of the investigated cities, climate data and traffic flow, see Fig. 3.
In this paper, a BEV and an ICEV with compact dimensions are chosen. Their main specifications are shown in Table 2. Furthermore, the required range, which was calculated in (5), should be reached any time of the year. Seasonal changes in climate conditions lead to varying demand for the air conditioning / heating. Hence, the month that results in the highest energy consumption is considered for determining the size of the battery pack.

# 5 Results

The EMPI are calculated with current data for 46 major cities and an assumed cost of 560 USD/kWh for the battery pack. These results, with the breakdown of each KPI introduced in 3.1, are shown in Fig. 4. There are big differences regarding the current potential for sustainable introduction of BEV depending on local conditions. While the majority of the cities considered already meet or exceed the critical value of EMPI = 50, some of the big cities from developing countries in

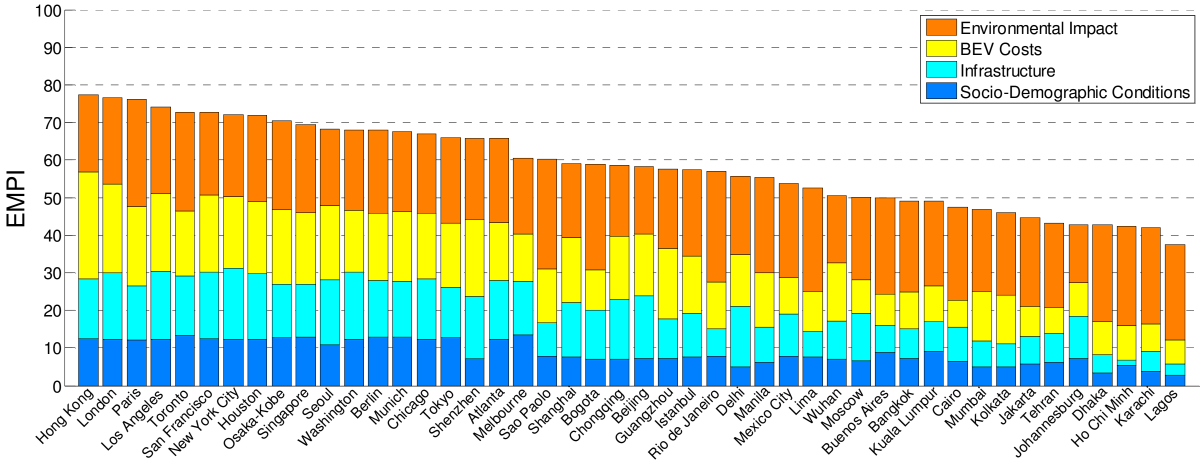


Figure 4: Electromobility Potential Index for 46 major cities

Asia and Africa currently do not show the appropriate conditions for sustainable electromobility. This is mainly due to the poor results with regards to the economic aspects and the lack of favorable infrastructure. It can be seen that the 18 highest scores with EMPI > 65 are widely distributed between wealthy cities in North America, Europe and Asia. None of the cities currently show perfect boundary conditions for the introduction of BEV. The best-performing cities with an EMPI > 75 are Hong Kong, London and Paris showing not only favorable, but also well-rounded local conditions for the introduction of electric vehicles.

Furthermore, while most cities show rather high contributions from $KPI_{\mathrm{E}}$, there is much room for the lower-ranked cities to improve in the areas represented by $KPI_{\mathrm{I}}$ and $KPI_{\mathrm{C}}$. The $KPI_{\mathrm{I}}$ can be increased by investing in favorable infrastructure, and taking into consideration factors that cannot be changed, such as the wealth of a city or the fixed costs of a vehicle, while an improvement in the $KPI_{\mathrm{C}}$ may be translated simply to offering economic incentives.

# 6 Sensitivity Analysis

## 6.1 Influence of city parameters

The EMPI is determined based on twenty different city parameters (see Fig. 2 & 3), which are obtained from a variety of different sources. The data obtained from sources such as the UN [15], [16] or reputable organizations [17], [18] are considered trustworthy. However, the reliability of the sources for some other city parameters cannot be guaranteed.

The *Average Speed*, in [1] identified as a major influence factor, cannot be acquired from a single global source, but instead needs to be obtained from various sources, the correctness of which is hard to prove. Furthermore, the variability of some other parameters, especially *Fuel Price*, makes it difficult to fix a value, as the local fuel prices have the tendency to vary on a day-to-day basis.

Thus, the effects of varying *Average Speed* and *Fuel Price* are investigated in order to determine how inaccurate data influence the EMPI.

Fig. 5 shows the variations on the EMPI by altering the *Average Speed* by ± 5 km/h and *Fuel*

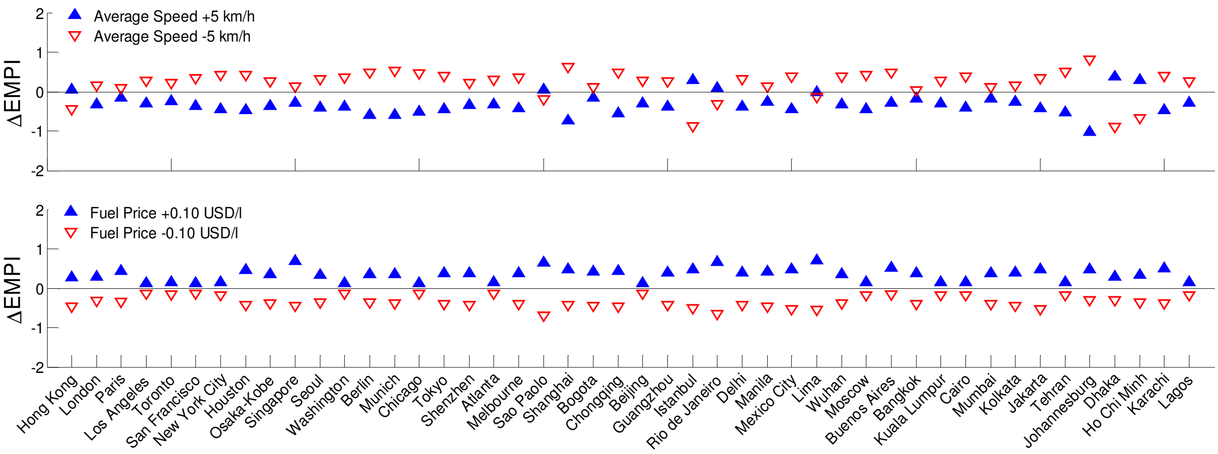


Figure 5: Effects of variations in *Average Speed* and *Fuel Price* on EMPI

Table 3: Expected uncertainties of city parameters

| City Parameter | Uncertainty |
|---|---|
| Average Speed | ± 5 km/h |
| Fuel Price | ± 0.10 USD/l |
| Energy Price | ± 0.03 USD/kWh |
| GDP / capita | ± 2000 USD |
| Government Encouragement Index | ± 0.11 |
| Infrastructure Development Index | ± 0.11 |
| Road Length | ± 500 km |
| Rail Length | ± 25 km |
| Motor Vehicle Ownership | ± 3 % |

*Price* by ± 0.10 USD/l. It can be observed that the ΔEMPI are very small, almost always within ± 1.

Table 3 lists all the city parameters that have to be obtained from non-verified sources as well as the uncertainties expected for each of the values. The values for each of the uncertainties are chosen based on either the differences in parameter values obtained from various sources, a percentage (5-10%) of the total range recorded for each parameter across all the different cities, or a suitable combination of both.

Fig. 6, which depicts the resulting range of EMPI results considering all the above parameter uncertainties, shows that small variations in the city parameters only have a minor effect on the overall EMPI. This proves the robustness of the tool.

## 6.2 Influence of weighting factors

As mentioned in 3.2, the weightings $g_{\mathrm{i}}$ of the four $KPI_{\mathrm{i}}$, i={E,C,I,S}, are determined subjectively by the authors. In order to determine the robustness of the EMPI, the influences of the weighting factors $g_{\mathrm{i}}$ are investigated.

Changing one weighting factor $g_{\mathrm{i}}$ by $\Delta g_{\mathrm{i}}$ will result in a change of the remaining weightings by $\Delta g_{\mathrm{j \neq i}} = \frac{-\Delta g_{\mathrm{i}}}{1-g_{\mathrm{i}}} g_{\mathrm{j}}$. Hence, the EMPI will change by

$$\Delta EMPI_i = \Delta g_i KPI_i - \frac{\Delta g_i}{1-g_i} \sum_{j \neq i} g_j KPI_j. \qquad (6)$$

The plots shown in Fig. 7 show the effects on the EMPI when manipulating the initial weighting factors each by $\Delta g_{\mathrm{i}} = 10\,\%$, i={E,C,I,S}. The cities are arranged such as in Fig. 4. Three main insights can be gained from Fig. 7.

Firstly, the changes in the absolute EMPI value are rather small.

Secondly, for cities on the higher end of the EMPI scale as shown in Fig. 4, changes in the weighting factors only affect the EMPI insignificantly (ΔEMPI < 3). For these cities, each of the KPI have high unweighted contributions to the overall EMPI, with no single KPI being dominant.

Thirdly, on average, an increase in $g_{\mathrm{E}}$ results in an overall increase in the EMPI, while an increase in $g_{\mathrm{C}}$ or $g_{\mathrm{I}}$ leads to an overall decrease. This effect is more pronounced for cities with lower EMPI results. In these, the contribution of $KPI_{\mathrm{E}}$ is comparably high, as is the case with almost all of the cities, whereas the contribution of $KPI_{\mathrm{I}}$ is significantly low, see Fig. 4. Thus, an increase in $g_{\mathrm{C}}$ or $g_{\mathrm{I}}$ would exaggerate this low contribution and lead to a decrease in overall EMPI, while an increase in $g_{\mathrm{E}}$ would instead cause the opposite.

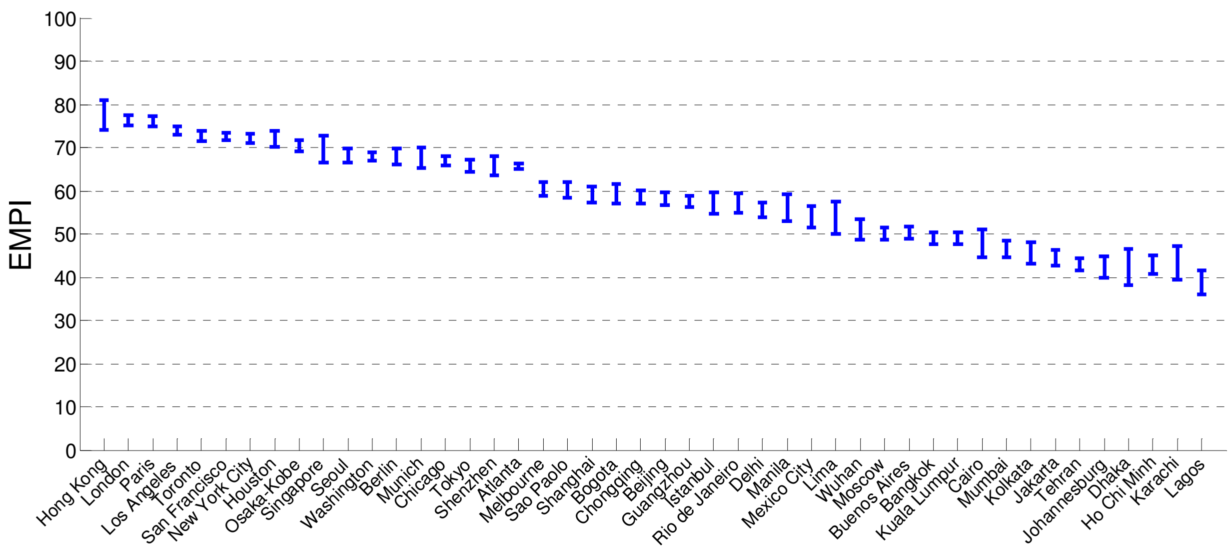


Figure 6: Range of EMPI results considering uncertainties in city parameters

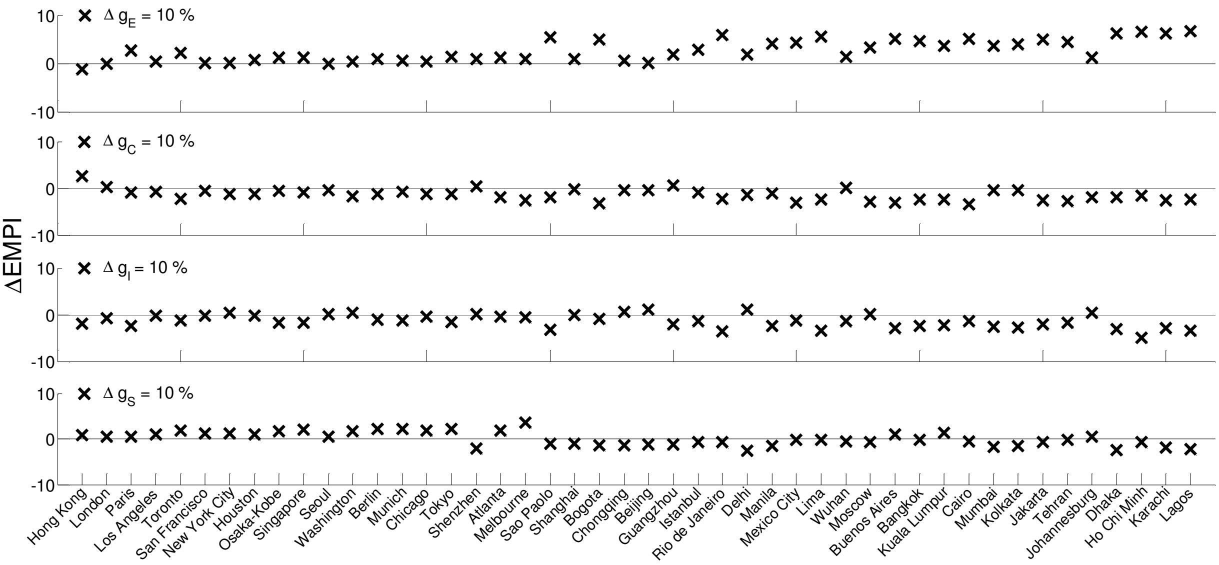


Figure 7: Effects of variations in weighting factors on EMPI

# 7 Correlation Analysis & Discussion

In order to find correlations, graphs of all city parameters were plotted against the EMPI. A selection of these plots is presented in Fig. 8. The lines represent the second order best fit curves and ρ the correlation coefficient of the data to each of the respective curves.

Fig. 8a shows the relatively low correlation ($\rho = 0.48$) between the average speed and the EMPI, whereas in [1] a high correlation was stated. This discrepancy is due to the usage of the fixed range of 150 km in [1] and the range requirement calculated from (5) for the reference BEV. In [1], a lower average speed reflects negatively on the EMPI, because the main effect it had was to increase the energy consumption due to air conditioning/heating.

As explained in 4.1, one of the main new features of the updated tool is the variable BEV, in which range and thus battery size are determined with reference to the average speed. Slow traffic still raises the energy consumption for air-conditioning/heating and auxiliaries, although the lower weight due to the smaller battery would lead to a lower consumption in terms of the drivetrain. The local climate conditions thus determine which of the above effects have a bigger impact on the overall energy consumption.

The energy consumption does not only affect the *Environmental Impact* ($KPI_E$), but also the *BEV Costs* ($KPI_C$) in terms of the running costs of a BEV. A smaller battery would also significantly

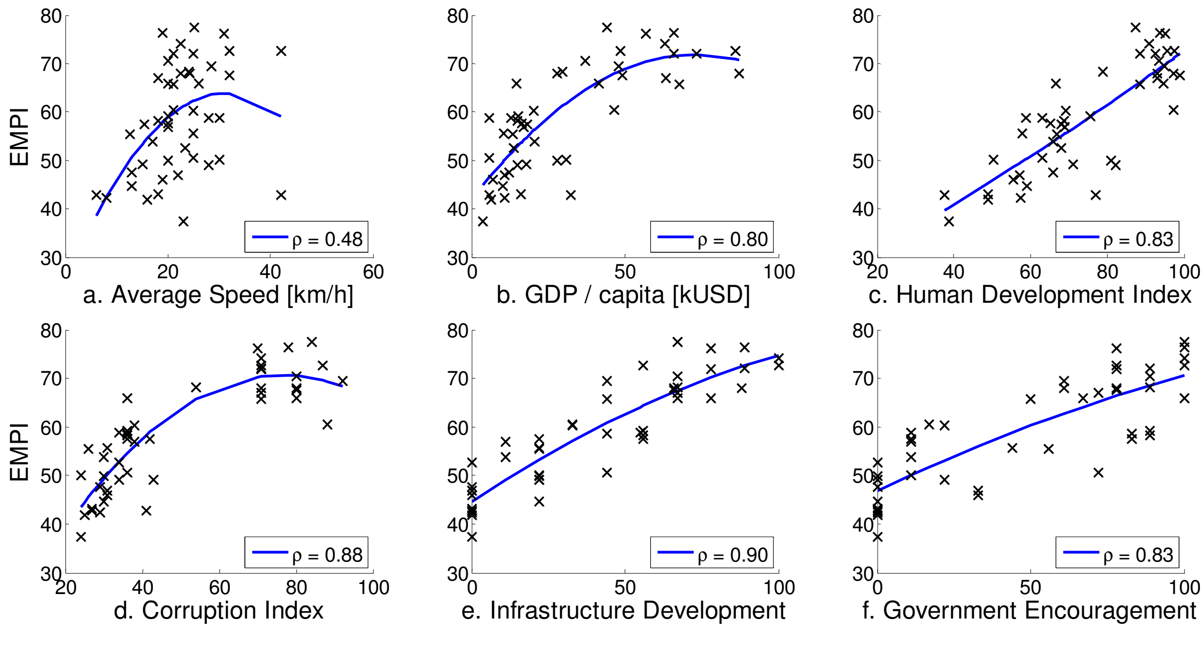


Figure 8: Correlations of selected city parameters with EMPI

lower the initial costs, which in turn leads to a higher $KPI_C$.

Referring to Fig. 8a and the non-correlating values, it can be deduced that the described effects regarding both the environmental and economic aspects even out. Furthermore, the results highlight the importance of adapting the required vehicle ranges to the local traffic conditions. By doing that, the influence of the average speed on the EMPI result is almost negligible.

The high correlation ($\rho = 0.8$) of the economic city parameter, *Gross Domestic Product (GDP) per capita*, shows that wealthy cities currently show the best boundary conditions for electromobility.

The inputs that exhibit the highest correlations with the EMPI are the man-made indices rather than explicit city parameters, seen in Fig. 8c-f. *Human Development Index* [15], Fig. 8c, and *Corruption Index* [16], Fig. 8f, are existing indices, while *Infrastructure Development Index*, Fig. 8d, and *Government Encouragement Index*, Fig. 8e, were introduced in [1]. The correlations of these indices show that cities with high living standards, well-developed infrastructure and reliable governance currently show the best boundary conditions for the successful and sustainable introduction of BEV.

# 8 Conclusion

This paper has presented an improved methodology for the EMPI, and has proven that the approach is stable and robust.

Even though the values of the weighting factors are subjectively defined, changing them has little impact on the EMPI.

Small changes in the values of selected city parameters have also been shown to have a minor effect on the EMPI, allowing for slight discrepancies during data gathering.

Furthermore, the added feature of a matched BEV based on the average speed showed that the potential success of BEV is not dependent on the traffic flow per se, but instead on the adaptation of BEV specifications to precisely suit the requirements of the city. Even with today's technologies, BEV can be successfully and sustainably introduced in cities with any traffic condition as long as the range is adapted to the real needs of the city and not overextended to the longest range possible. Whether or not these BEV will eventually show sustainable success depends on other factors, mainly on the economic aspects and on the existence of favorable infrastructure.

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