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The evolution of dynamic interactions between the knowledge development of powertrain systems

ABSTRACT

Competition in the already highly competitive automotive industry intensified in the early 1990's. The ubiquitous internal combustion engine began to be challenged by the upstart alternatives of battery and hybrid electric vehicles, which has led to an intricate web of knowledge development. Our research aims to qualify and quantify the dynamic relationships that formed in the knowledge development of powertrains by adopting conceptual insights from evolutionary ecology. Specifically, the interdependent relationships observed in the Technological Innovation System (TIS) framework is similar to that between species such that powertrain systems can either support or inhibit the knowledge growth of one another over time. Our theoretical framework extends the economics of technical change within technologies vis-à-vis the concept of 'positive and negative externalities' and 'knowledge development co-dynamics'. We use patents data extracted from Thomson Reuters' Derwent Innovations Index to measure the knowledge development in each technological field and apply the biological Lotka-Volterra (L-V) model to analyse the data across three separate time periods 1985-1996, 1997-2007, and 2008-2016. Our results show that the behaviour of the powertrain systems change over time as they have behaved as creative (or uncreative) and explorative (or exploitative). We also demonstrate that the powertrain systems go through temporal transitions where the relationship mode between them changes between amensalism, parasitism, commensalism, and symbiosis. In line with this we recommend that policy makers not only devise strategies (offensive or defensive) for each interaction modes but to also consider changing their strategies when there is transition between the modes. Furthermore, policy makers should consider the dual role of 'creation' and 'destruction' in their innovation policy mixes.

Keywords: Technological innovation system; Powertrain technologies; Knowledge development; Dynamic interaction; Patent analysis; Lotka-Volterra equations

JEL O32; O33; L62; Q55

1. Introduction

Ever since humans first learned to harness fire, technological evolution and innovation has played a crucial role in driving both economic and social change (Coccia, 2019d). While evolution is generally considered to be the "progressive growth of a system that generates a transition from simple to complex system in nature and society" (Coccia, 2019c, p1), understanding how technologies evolve over time can be complex and problematic (Arthur, 2009). This is true in studying the evolution of vehicle powertrain technologies, which traditionally have involved a large number of environmental, organisational, political and technological factors (Dijk et al., 2016; Høyer, 2008). Using the technology definition by Coccia (2017), the incumbent powertrain of internal combustion engine vehicle (ICEV) can be defined as a complex system which is comprised of several components and sub-systems such as combustion engine, fuel and exhaust systems and transmission (Poullikkas, 2015) that are connected with one another in a way that the system has satisfied the transportation needs of modern society. The introduction of the battery electric vehicle (BEV) powertrain was a disruptive technology that replaced the entire components and sub-systems found in ICEV with batteries, charger, power convertor and controller, traction motor etc. However, the hybrid electric vehicle powertrain (HEV[1]) created a transitionary alternative, as this powertrain hybridises the components and sub-systems of both ICEV and BEV (Poullikkas, 2015).

It has been often pointed out that the process of technological evolution closely resembles that of biological evolution (Arthur, 2009; Basalla, 1988; Coccia, 2017, 2019b,c,d; Kauffman and Macready, 1995; Mirzadeh Phirouzabadi et al., 2020a; Mirzadeh Phirouzabadi et al., Unpublished results; Solé et al., 2011), and while technological evolution is (for now) not capable of self-production it is driven by the Generalized Darwinism concepts of variation, selection and retention (Coccia, 2019a,b; Solée et al., 2013). Furthermore, technological evolution can also include aspects of tinkering, convergence, and contingency in biological evolution, especially when cost/or energy is constrained for optimisation (Solée et al., 2013). In line with this perspective several studies have argued that evolution, whether biological or technological, is a narrative of coevolution as the adaptive alterations of one technology can influence the landscape of other neighbouring technologies (Coccia, 2017, 2019d,e; Kauffman and Macready, 1995). For example, we can observe that the technological evolution and advancement within the components of both ICEV and BEV has over time improved the components of the hybrid powertrain of HEV (Dijk, 2014; Dijk et al., 2015; Köhler et al., 2013). As such technological evolution is not a simple linear process about a single entity but is rather a story of co-evolution between technologies (Coccia, 2019b).

The analysis of most studies in the literature, however, either did not include both positive and negative influences that one powertrain has on the knowledge growth of other powertrains, or when included, they only assumed a pre-defined constant positive influence between them (Al-Alawi and Bradley, 2013). Our article addresses the literature shortcoming by exploring the behaviour and evolution of a powertrain technology interactions and their dependence on other powertrain technologies for knowledge development. We explore the supportive and inhibitive forces between the knowledge growth of the powertrain systems by conceptualising the Technological Innovation System (TIS) framework and quantifying the biological models using Lotka-Volterra (L-V) equations. We measure the state of knowledge development of each technological field through patents data extracted from Thomson Reuters' Derwent Innovations Index (DII) for the three separate time periods 1985-1996, 1997-2007, and 2008-2016. Our theoretical framework extends the economics of technical change within technologies vis-à-vis the concept of '*positive and negative externalities*' and '*knowledge development co-dynamics*'.

This article is structured as follows. Section 2 presents the theoretical background and literature. Section 3 elaborates data collection and analysis method. Section 4 presents results and findings. Finally, our discussion and conclusions are presented in Section 5.

2. Literature review

Technological evolution can be defined as the gradual growth of a system that involves a transition from simplicity to complexity not only in terms of intra-component interactions (i.e. the linkages between one's own component and sub-systems) but also in terms of inter-systems interactions (i.e. the relationships with other associated systems) (Coccia, 2019b,c; Simon, 1991). In order to satisfy the increasing needs of humans in society, both the intra- and inter- systems interactions are necessary. The interaction between multiple technologies in the innovation and transition literature is described in three types (Andersen and Markard, 2019): intra-sector technology interaction (Geels, 2018; Markard and Hoffmann, 2016), inter-sector technology interaction (Arthur, 2009; Murmann and Frenken, 2006), and cross-sector technology interaction (Rosenbloom, 2019). This has included work on nested hierarchies of interrelated technological components (Clark, 1985; Simon, 1962); technology- and sector-level complementarities (Haley, 2018; Markard and Hoffmann, 2016); interplay between upstream and downstream parts of the value chains (Sandén and Hillman, 2011); and multiple niche-regime interaction (Geels, 2002; Raven and Verbong, 2007). The research in this field has conceptualised the co-evolution and interaction of multiple technologies into two main strands, the Multi-Level Perspective (MLP) and the Technological Innovation System (TIS) framework (Andersen and Markard, 2019; Markard and Truffer, 2008).

The MLP approach conceptualises the pure symbiotic and competitive interplays between niches (emerging technologies) and regime (incumbent technology) within the landscape (environment) (Geels, 2002). Competition occurs when niches and regime have a negative effect on one another; and symbiosis when they affect one another positively. This has been frequently applied to historical case studies to investigate four generic transition pathways based on the timing and nature of interactions between the three levels (Geels and Schot 2007a):

- Reproduction pathway: moderate landscape pressure occurs at the moment a symbiotic relationship is shaped between an underdeveloped niche and a well-powered regime.
- De-alignment and re-alignment pathway: large landscape pressure occurs at the moment a symbiotic relationship is shaped between an underdeveloped niche and an ill-powered regime.
- Substitution pathway: large landscape pressure occurs at the moment a competitive relationship is shaped between a well-developed niche and a well-powered regime, and
- Re-configuration pathway: large landscape pressure occurs at the moment a competitive relationship is shaped between a well-developed niche and an ill-powered regime.

The pure competitive or symbiotic relationship conceptualised in the MLP approach is limited to the traditional theories of technological evolution such as Porter (2008)'s diamond model, or Fisher and Pry (1971)'s substitution model, which only formulate the symmetric relationships between technologies. Alternatively, the new theories of technological evolution— e.g. the predator-prey approach (Farrell, 1993), the theory of technological parasitism and virus technologies (Coccia, 2017, 2019b,c,d), and the multi-mode technology interaction theory (Mirzadeh Phirouzabadi et al., 2020a; Mirzadeh Phirouzabadi et al., Unpublished results; Pistorius and Utterback, 1997; Sandén and Hillman, 2011)— borrow and include the more nuanced (and asymmetric) relationships defined between biological species. These relationships include parasitism, commensalism, amensalism, and neutralism (Coccia, 2019d; Farrell, 1993; Mirzadeh Phirouzabadi et al., Unpublished results; Pistorius and Utterback, 1997; Sandén and Hillman, 2011). Parasitism occurs when one technology has a positive impact on the other and a negative impact on the other; commensalism occurs where there is a positive impact for one but the other is not affected; amensalism occurs when there is a negative effect for one but the other is not affected; and finally neutralism occurs when there is no effects on either technology. The new theories of technological evolution compare and resemble technological evolution to biological evolution due to some reasons. First, according to Arthur and Polak (2006)'s definition of technology[2], the build-up of complex technologies depends on the existence of simpler, earlier technologies that have been developed for intermediate or simpler societal needs. This mirrors the observations in biological evolution by Lenski et al. (2003) that the creation of complex features and functions depends on the existence of simpler features and functions that have been first favoured and acted as steppingstones. Second, the Generalized Darwinism concepts of variation, selection and retention can explain how the nature of innovation processes as well as the evolution of complex technologies evolve (Bryan et al., 2007; Coccia, 2019b; Hodgson and Knudsen, 2006; Solée et al., 2013). This conceptualisation is used to define the various stages of technological life cycle (Murmann and Frenken, 2006): i.e. a sequence of an era of ferment (variation), an era of dominant design (selection), and an era of incremental innovation (retention). Last but not least, both biological and technological evolutions involve cost/energy constraints since efficiency is a common important factor for driving improvements in both biological and technological systems due to limited resources (Solée et al., 2013).

Based on the new theories of technological evolution, the second major strand of research the TIS framework conceptualises the co-evolution and interaction of multiple technologies by accommodating all the six biological relationship modes. The innovation systems approach generally focuses on the structures and dynamics that support or inhibit the emergence of innovation at national, regional, sectoral and technological level (Markard and Truffer, 2008). In particular the TIS framework conceptualises the structures and dynamics that support or inhibit the knowledge growth of technologies vis-à-vis *knowledge development dynamic* and *knowledge development co-dynamic*[3]. The TIS knowledge development dynamic is related to processes and activities that are endogenous to a single technology and reinforce or deteriorate the knowledge evolution (performance) of the technology (Hekkert et al., 2007; Markard and Truffer, 2008). The knowledge in a TIS is built through positive internal feedback such as early investments and economies of scale and learning (Mirzadeh Phirouzabadi et al., Unpublished results; Sandén and Hillman, 2011) and negative internal feedback such as resource dwindles (Sandén and Hillman, 2011) and reaching technological performance ceiling (Papachristos, 2017). According to this framework, the growth in a powertrain technology can support or inhibit the growth in the other powertrain technologies over time as per the biological relationship modes (Mirzadeh Phirouzabadi et al., 2020a; Mirzadeh Phirouzabadi et al., Unpublished results; Sandén and Hillman, 2011). It is, hence, possible for the knowledge dynamic in one TIS to be influenced by and coupled to the knowledge dynamic in another TIS, called *knowledge development co-dynamics*. This way the TIS's knowledge can be built through positive external feedback mechanisms such as knowledge spillovers from other TISs (Noailly and Shestalova, 2017) or negative external feedback such as intense competition over sources or ideas with other TISs (Carnabuci, 2010; Mirzadeh Phirouzabadi et al., Unpublished results) or the dismantling of its knowledge networks by external actors (Castiaux, 2007; Kivimaa and Kern, 2016; Mirzadeh Phirouzabadi et al., Unpublished results). Ultimately, the combined and accumulated positive and negative feedback of the TIS, whether endogenous or exogenous, generate the complete S-shaped curve of TISs (Pistorius and Utterback, 1997; Sandén and Hillman, 2011).

In addition to the two conceptual streams of research, there are five quantification approaches that measure technological evolution and interactions (Magee, 2012): patent analysis (Borgstedt et al., 2017; Oltra and Saint Jean, 2009); journal and magazine articles analysis (Bohnsack et al., 2015; Sarasini, 2014); market share (Eppstein et al., 2011; Pasaoglu et al., 2016; Sullivan et al., 2009); major innovation counts (Sick et al., 2018); and technical capability dynamics (Zhang et al., 2019a). The *bibliometrics analysis* approach uses trade journal articles or magazines as a source of basic research activities to measure the scientific knowledge performance in the field of powertrain technologies (Bohnsack et al., 2015; Sarasini, 2014; Sick et al., 2018; Watts and Porter, 1997). For example, Bohnsack et al. (2015) used the archival data of various magazines[4] to investigate the recurring waves of carmakers' low-emission-vehicle investments on local, national and international levels and accordingly explored the influence of geographically bound government policies on carmakers' innovation strategies. The *patent analysis* approach uses patents data as a source of applied research and development activities to measure the technological knowledge performance in technology life cycle (Sick et al., 2018; Watts and Porter, 1997). There are quite a number of studies that have applied the patent analysis approach to investigate the technological evolution of powertrain technologies (Barbieri, 2016; Borgstedt et al., 2017; Choi, 2018; Faria and Andersen, 2017a; Faria and Andersen, 2017b; Mirzadeh Phirouzabadi et al., 2020a; Oltra and Saint Jean, 2009; Sarasini, 2014; Sick et al., 2016; Wesseling et al., 2014a; Wesseling et al., 2015). For example, investigating the chronological patenting share of car manufacturers it is observed that their strategy has been more converged towards green ICEV-related innovations than HEV or BEV (Faria and Andersen, 2017a; Faria and Andersen, 2017b).

The *major innovation counts* approach explores the chronological major innovations in the automotive industry using for example concept models, prototypes, products launches, and start-up companies (Sick et al., 2018; Sierzchula and Nemet, 2015; Watts and Porter, 1997; Wesseling et al., 2015). Sick et al. (2018) gained insight into the transition from R&D phase to application phase in the battery technology life cycle by exploring the state of new product launches and start-up companies over time. However, their analysis was less in depth and in details as it was predominantly based on the raw number rather than the content of new product launches and start-up companies. The *technical capability dynamics* approach quantifies not only the value of a given incremental improvement built in a technology but also the role of material innovations in overall technological evolution (Magee, 2012). Technical capability is defined as a performance measure for a key technical function that the technology is intended to achieve. The metrics used in this approach are more technical than managerial such as speed, capacity, and energy efficiency (Zhang et al., 2019a). For example, while the BEV powertrain converts 59%–62% of the electrical energy from the grid to power at the wheels, the energy efficiency of ICEV is between 17%–21% (Zhang et al., 2019a). This approach is useful when there's a technical improvement in any hierarchical part of a technological system and the aim is to identify its trickle-down or trickle-up effects between the system technology (e.g. the BEV powertrain), the component technology (e.g. battery) and the fundamental technology (e.g. superalloys) (Zhang et al., 2019a; Zhang et al., 2018).

The last approach, *market share* analysis, deals with the diffusion or the penetration rate of powertrain technologies in market using various modelling approaches (Al-Alawi and Bradley, 2013) such as agent-based model (Adepetu et al., 2016; Pasaoglu et al., 2016; Sullivan et al., 2009), consumer choice model (Javid and Nejat, 2017; Rezvani et al., 2015; Santini and Vyas, 2005; Shepherd et al., 2012; Struben, 2006), and diffusion and time series model

(Muraleedharakurup et al., 2010; Trappey and Wu, 2008). For example, the studies using diffusion and time series model investigated and forecasted the rate at which powertrain technologies are adopted and diffused in market through the diffusion models of Bass (Cao, 2004; Jeon, 2010), Gompertz, and Logistic (Muraleedharakurup et al., 2010; Trappey and Wu, 2008). Or the studies using consumer choice model compared the market penetration rate of powertrain technologies in terms of consumer's preferences and limits using multinomial logit model (MNL) and nested multinomial logit model (NMNL) (Rezvani et al., 2015; Santini and Vyas, 2005; Struben, 2006).

While each of the five quantification approaches has several different advantages, they still suffer from some shortcomings. The studies using the bibliometric and patent approaches only investigated the scientific or technological trend and pattern of powertrain technologies individually, and accordingly compared them in terms of the number of publications or patents or the number of backward or forward citations. Bibliometric data, in particular, can only cover the early stage of technology life cycle and are not able to represent a full and exhaustive innovation or technological progress of R&D activities. The main drawbacks of the major innovation counts approach are that not only there is a lack of objectivity as to what is included as innovation, but also there's a lack of statistical method as to how an in-depth innovation content should be measured (Magee, 2012). With regard to the technical capability dynamics approach, it's argued that the technical performance metrics used by the studies generally evolve much slower than the business performance metrics (such as patents, cost, price, production, sales revenue, and profit) and they are less factual than the business metrics (Zhang et al., 2019c). This is because the technical performance metrics are not collected and published in a periodic manner (i.e., quarterly or yearly) and the proprietor of the data usually retains only the greatest performance value in each time period (Zhang et al., 2019c). Finally, while the studies using the market share approach are quite well established in describing the market behaviour of powertrain technologies, their analysis often does not focus on the technical and technological improvements over time (Magee, 2012).

From the literature, it is observed that the majority of the quantification studies did not include both the positive and negative influences on the knowledge growth of other powertrains, and when the interaction was included, they only assumed a pre-defined constant positive influence between them (Al-Alawi and Bradley, 2013). This is because the technological development of powertrain technologies are mostly associated to factors such as oil price (Barbieri, 2016), suppliers' capabilities (Borgstedt et al., 2017), infrastructure (Dijk et al., 2015), carmakers' strategies (Wesseling et al., 2015), increasing returns (Sierzchula et al., 2015), and legitimisation (Sierzchula et al., 2015). So, they come short at uncovering and analysing the dynamic interactions between powertrain technologies in the form of both positive and negative influences over time.

3. Methodology

We measure the state of knowledge development of each technological field through patents data extracted from Thomson Reuters' Derwent Innovations Index (DII). While many studies using the patent analysis approach have not addressed the problem of multi-technology interactions for powertrain technologies, the approach is still worth pursuing as patents data remain the best and most appropriate source of knowledge data. First, patents data are known as the best available indicator for the R&D outcome of a car manufacturer in the industry (Oecd, 1994). Second, the inventions in a similar technological field can be easily distinguished as car manufacturers do not usually distinguish between the budget that they allocate to each powertrain technology (Sierzchula and Nemet, 2015). Third, we are able to observe the technological change and progress of a powertrain technologies in the form of a time series analysis due to availability of yearly numbers (Borgstedt et al., 2017). This is especially crucial for emerging disruptive powertrain technologies such as BEV as their patent-based life cycle provides richer information than sales-based life cycle (Faria and Andersen, 2017b). Finally, patents data as a business performance metric are superior to the technical performance metrics e.g. speed or energy efficiency due to their faster evolution and more factual nature (Zhang et al., 2019c).

However, there are a number of restrictions when it comes to using the number of patents data as a proxy for knowledge development. First, not all inventive or innovative activities in an industry emerge as patents (Borgstedt et al., 2017; Oltra and Saint Jean, 2009). Second, there are differences between national patenting systems in terms of laws and rules, e.g. the required degree of novelty (Borgstedt et al., 2017; Oltra and Saint Jean, 2009). Last, it can be a cumbersome process to read and verify the quality and content of patents for their appropriateness for analysis (Barbieri, 2016).

We have attempted to minimise these restrictions by using the original, comprehensive patents database provided by Mirzadeh Phirouzabadi et al. (2020a) and Mirzadeh Phirouzabadi et al. (2020b). For the first restriction, it has been showed that a relatively high share of inventions in the automotive industry is actually patented by the players since the industry strongly relies on patents as a means to protect against imitations (Cohen et al., 2000). For the second restriction, the patent database was extracted from Thomson Reuters' Derwent Innovations Index (DII) as one of the largest patent databases with access to over 80 granting authorities worldwide. For the last restriction, they adopted a combined search strategy of patent classifications and keywords (Appendix A) in order to accurate their patents database. The data was processed not only based on 'patent families[5]' to avoid the multiple counting of the same inventions (Borgstedt et al., 2017, p78), but also based on 'priority date[6]' to avoid any additional lags, e.g. 18 months on average (Barbieri, 2016). The authors additionally conducted a manual validity check for at least 5% of the patents to verify the quality of the results[7] (Borgstedt et al., 2017).

The annual state of technological knowledge development of powertrain (i) during a single year (t) (T=1985, …, 2016) is calculated in our research by the sum of patents that have been granted in its technological field during year (t) (Eq. 1):

$$PAT_{i,t} = \sum_{t} PAT_i \tag{1}$$

To quantify the multi-technology interactions, or in our particular case the supportive and inhibitive forces between the knowledge growth of the powertrain systems, we introduce and apply the Lotka-Volterra (L-V) equations model, which was originally used to compute the intra- and inter-population interactions among biological species (Lotka, 1926; Volterra, 1927). The L-V equations are applied to calculate both the endogenous and exogenous knowledge growth of the interacting technologies over time (Mirzadeh Phirouzabadi et al., 2020a; Pistorius and Utterback, 1997; Sandén and Hillman, 2011; Zhang et al., 2017), such as skyscraper and cement technologies (Zhang et al., 2017, 2018), cutting-edge fusion technologies, and high value-added service technologies (Lee and Kim, 2010), and vehicle powertrains (Mirzadeh Phirouzabadi et al., 2020a; Sun and Wang, 2018). The equations are demonstrated to be comprehensive enough to produce the solution sets of a variety of standard mathematical forecasting functions[8] that are used in the field of powertrains, such as simple or decaying exponential functions, Logistic (e.g. for ICEV's growth rate by Song and Aaldering (2019)), Bass (e.g. for HEV's rate of adoption by Mcmanus and Senter Jr (2009)), and

Gompertz (e.g. for HEV's rate of adoption by Muraleedharakurup et al. (2010)). Additionally, the L-V parameters can be considered as the descriptors of the causal factors of technological changes and evolution in the field of powertrain technologies e.g. R&D investment and government policy (Zhang et al., 2017).

The following equations show the L-V equations which were originally proposed for the case of continuous data. Here for brevity we only describe the parameters for the ICEV powertrain and its interaction with HEV and BEV as expressed in Eq. 2. The parameters used in Eq. 3 and 4 have the same definition but are only applicable for HEV and BEV, respectively.

$$\begin{aligned}\frac{d(PAT_{ICEV,t})}{dt} &= \big(a_{ICEV} - b_{ICEV}(PAT_{ICEV,t}) - c_{ICEV,HEV}(PAT_{HEV,t}) \\ &\quad - c_{ICEV,BEV}(PAT_{BEV,t})\big)(PAT_{ICEV,t}) \\ &= a_{ICEV}(PAT_{ICEV,t}) - b_{ICEV}(PAT_{ICEV,t})^2 \\ &\quad - c_{ICEV,HEV}(PAT_{HEV,t})(PAT_{ICEV,t}) \\ &\quad - c_{ICEV,BEV}(PAT_{BEV,t})(PAT_{ICEV,t})\end{aligned} \tag{2}$$

$$\begin{aligned}\frac{d(PAT_{HEV,t})}{dt} &= \big(a_{HEV} - b_{HEV}(PAT_{HEV,t}) - c_{HEV,ICEV}(PAT_{ICEV,t}) \\ &\quad - c_{HEV,BEV}(PAT_{BEV,t})\big)(PAT_{HEV,t}) \\ &= a_{HEV}(PAT_{HEV,t}) - b_{HEV}(PAT_{HEV,t})^2 \\ &\quad - c_{HEV,ICEV}(PAT_{ICEV,t})(PAT_{HEV,t}) \\ &\quad - c_{HEV,BEV}(PAT_{BEV,t})(PAT_{HEV,t})\end{aligned} \tag{3}$$

$$\begin{aligned}\frac{d(PAT_{BEV,t})}{dt} &= \big(a_{BEV} - b_{BEV}(PAT_{BEV,t}) - c_{BEV,ICEV}(PAT_{ICEV,t}) \\ &\quad - c_{BEV,HEV}(PAT_{HEV,t})\big)(PAT_{BEV,t}) \\ &= a_{BEV}(PAT_{BEV,t}) - b_{BEV}(PAT_{BEV,t})^2 \\ &\quad - c_{BEV,ICEV}(PAT_{ICEV,t})(PAT_{BEV,t}) \\ &\quad - c_{BEV,HEV}(PAT_{HEV,t})(PAT_{BEV,t})\end{aligned} \tag{4}$$

$PAT_{ICEV,t}$ represents the annual state of technological knowledge development of ICEV in year t, and the derivative $\frac{d(PAT_{ICEV,t})}{dt}$ tracks the technological knowledge change rate of the powertrain. a_{ICEV} refers to the endogenous knowledge growth rate of ICEV when the powertrain is developing alone. The more positive the value of the knowledge growth rate of the powertrain the more likely the system emphasises knowledge creativity and variety (the more negative the value, the more likely the system opposes knowledge variety and lacks creativity) (Castiaux, 2007). The b_{ICEV} term refers to the internal interaction rate of ICEV when it is developing alone. The more positive the value of the internal interaction rate, the more likely the technological system tends to archive, control, maintain and exploit its knowledge (the more negative the value, the more likely the system emphasises emergent matters, flexibility and knowledge exploration in order to create radical innovations) (Castiaux, 2007). Together the endogenous knowledge growth rate and the internal interaction rate are used to calculate the system's carrying capacity. It describes a maximal limit or saturation point in the system's knowledge building that is imposed by the limited resources in the industry (Castiaux, 2007; Miranda and Lima, 2013). The more positive the carrying capacity, the more likely the environment is favourable to the powertrain; the more negative the carrying capacity, the more likely the environment is unfavourable to the powertrain as the required new resources are depleted[9] (Advani et al., 2018; Hui, 2006). The carrying capacity of the powertrain can be calculated[10] as k_{ICEV}=$a_{ICEV}/|b_{ICEV}|$. Table 1 shows the interpretation for the negative and positive values of ICEV's endogenous knowledge growth rate, internal interaction rate, and carrying capacity.

The third parameter is the external interaction parameter such as $C_{ICEV,HEV}$ which represents the rate at which the knowledge growth in ICEV is affected by HEV. The sign of this parameter determines which relationship mode is established between the interacting powertrains (see Table 2).

	Sign of parameter	
	+	-
a_{ICEV} endogenous knowledge growth rate	creative	uncreative
b_{ICEV} internal interaction rate	exploitative	explorative
k_{ICEV} carrying capacity	favourable environment with abundance of new resources	unfavourable environment with deplete of new resources

Table 1. Interpretation for the negative and positive sign of endogenous knowledge growth rate, internal interaction rate, and carrying capacity of ICEV

Mode of interaction	$C_{ICEV,HEV}$	$C_{HEV,ICEV}$	Description
Competition	+	+	Both powertrains have a negative influence on each other
Symbiosis	-	-	Both powertrains have a positive influence on each other
Neutralism	0	0	Neither affects the other
Parasitism	-(+)	+(-)	One has a positive influence on another, while the other has a negative influence (or vice versa)
Commensalism	0(-)	-(0)	One has a positive influence on another, while the other has no influence (or vice versa)

Amensalism	0(+)	+(0)	One has a negative influence on another, while the other has no influence (or vice versa)

Table 2. Modes of interaction between the two powertrains of ICEV and HEV (Pistorius and Utterback, 1997; Sandén and Hillman, 2011)

Eq. 2-4 are expressed for continuous data. Since our data is discrete (i.e. patent counts), we have transferred the continuous L-V equations to the discrete version proposed by Leslie (1958). Here we only express the discrete L-V equations for the case of ICEV as the formula is the same for the other two powertrains:

$$PAT_{ICEV,t+1} = \frac{\alpha_{ICEV}(PAT_{ICEV,t})}{1 + \beta_{ICEV}(PAT_{ICEV,t}) + \gamma_{ICEV,HEV}(PAT_{HEV,t}) + \gamma_{ICEV,BEV}(PAT_{BEV,t})} \tag{5}$$

Where $PAT_{ICEV,t+1}$ corresponds to $\frac{d(PAT_{ICEV,t})}{dt}$ expressed in Eq. (2), α_i corresponds to a_{ICEV}, β_{ICEV} to b_{ICEV}, and $\gamma_{ICEV,HEV}$ to $c_{ICEV,HEV}$ in the same equation. The continuous parameters in Eq. 2 can be calculated by the discrete parameters in Eq. 5 as follows:

$$a_{ICEV} = \ln \alpha_{ICEV} \tag{6}$$

$$b_{ICEV} = \frac{\beta_{ICEV} \ln \alpha_{ICEV}}{\alpha_{ICEV} - 1} \tag{7}$$

$$c_{ICEV,HEV} = \frac{\gamma_{ICEV,HEV} \ln \alpha_{ICEV}}{\alpha_{ICEV} - 1} \tag{8}$$

We estimate and calculate the discrete L-V parameters using the non-linear least-square method (Kim et al., 2006) via the two packages of Statistical Package for Social Sciences (SPSS version 25) and Microsoft Excel (version 16.23). We set the iteration convergence criterion set at 0.0001 using the Levenberg-Marquardt algorithm (Kim et al., 2006; Kreng et al., 2012). The initial value of, for instance, α_{ICEV} is set at 1, and the values of β_{ICEV} and $\gamma_{ICEV,HEV}$ at 0.001 (Choi et al., 2016).

In line with Mirzadeh Phirouzabadi et al. (2020a) and Mirzadeh Phirouzabadi et al. (2020b), we have chosen the time frame of 1985-2016 as our observation period since the year 1985 is known as a starting point for the sustainable development, mobility and transport discourses in the late 1980s (Høyer, 2008). The time frame ends in 2016 due to the data availability of patents since a patent application is published by a delay of 18 month starting with the priority date. To acquire a better fine-grained level of analysis and reveal the change of behaviour and evolution of the powertrain technologies, we have used the time frame segmentations[11] proposed by Mirzadeh Phirouzabadi et al. (2020a):

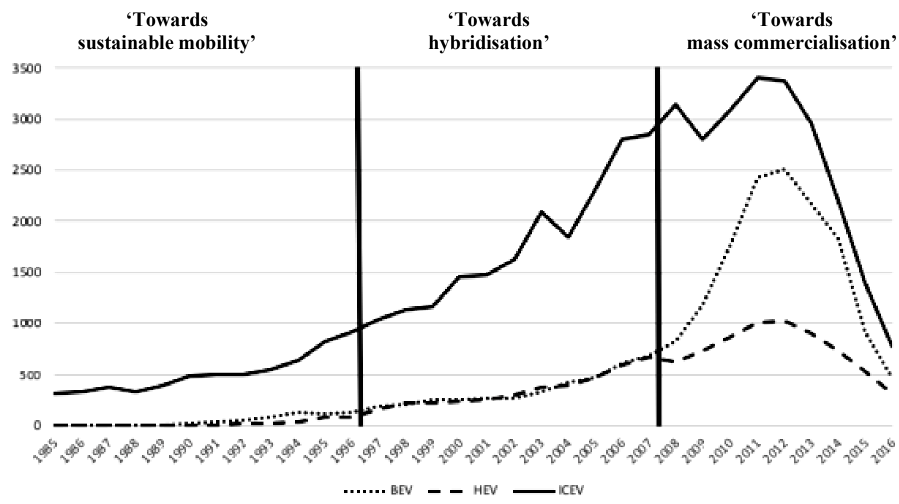
- Towards sustainable mobility (1985-1996): it covers the global warming and sustainable development discussions which led to the main environmental regulations such as the 1990 Clean Air Act Amendments and the 1990 California ZEV mandate, the introduction of the GM EV1, the establishment of institutions such as the 1991 U.S-based Advanced Battery Consortium 1991, the 1993 Partnership for a New Generation of Vehicles (PNGV) and the 1994 Automotive Research and Technological Development Master Plan (Høyer, 2008; Wesseling et al., 2014b).
- Towards hybridisation (1997-2007): it covers the demise of BEV in the early 2000s, the incremental improvements in ICEV, and the multiple relaxations and amendments of the ZEV mandate which led to not only the revival but also the mass production of HEV with Toyota Prius in 2000 (Magnusson and Berggren, 2011; Wesseling et al., 2014b).
- Towards mass commercialisation (2008-2016): it covers the immediate effects of the 2007 financial crisis as well as the 2005 fuel price rise, the 2012 ZEV mandate amendment, and the mass commercialisation of BEV with Mitsubishi i-MiEV (2009), Nissan Leaf (2010) and Tesla Roadster (2008) and Model S (2012) (Wesseling et al., 2014b).

4. Results

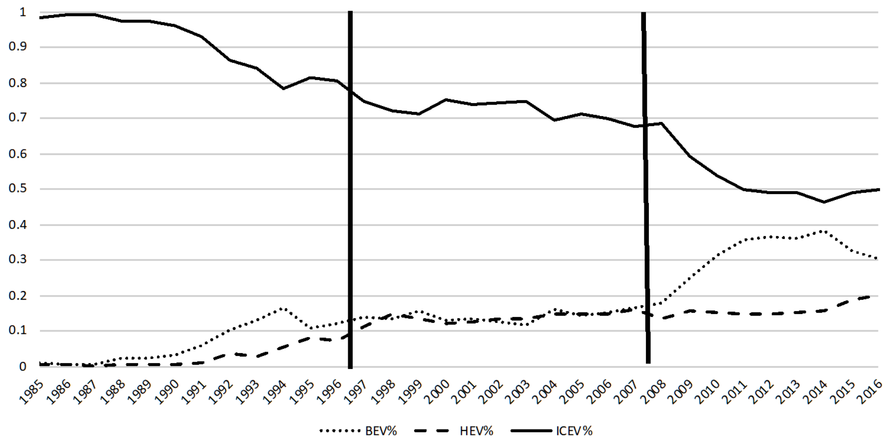
Table 3 and Figure 1 show the absolute and relative number of patents[12] over the entire period. Figure 1a shows that the number of patents for all the three powertrains have been growing between the early 90's and the early 2010's. Both BEV and HEV did not possess any patents until after the late 90's. Figure 1b depicts that the share of patents for HEV and especially for BEV has increased since the late 80's, and the share of patents for ICEV has been either decreasing or constant during the entire time frame. We can see from Figure 1a and 1b that the incumbent powertrain of ICEV never loses its dominant position to the other two powertrains during the entire period.

	Number	ICEV	HEV	BEV	Total
Towards sustainable mobility (1985-1996)	Absolute	6,200	262	595	7,057
	Relative	87.86%	3.71%	8.43%	100.00%
Towards hybridization (1997-2007)	Absolute	19,805	3,880	3,970	27,655
	Relative	71.61%	14.03%	14.36%	100.00%
Towards mass commercialization (2008-2016)	Absolute	23,149	6,746	14,125	44,020
	Relative	52.59%	15.32%	32.09%	100.00%
Entire period (1985-2016)	Absolute	49,154	10,888	18,690	78,732
	Relative	62.43%	13.83%	23.74%	100.00%
Validity check	Size	2,460	545	940	3,945
	Quality	87.25%	89.80%	88.25%	87.84%

Table 3 - The absolute and relative number of patents per powertrain and timespan adopted from Mirzadeh Phirouzabadi et al. (2020a)



(a) Absolute number



(b) Relative share

Figure 1 – The number and share of patents granted (1985-2016) (Mirzadeh Phirouzabadi et al., 2020a)

Table 4, Table 7, and Table 9 depict our estimation results for the first, second and third episode, respectively. Table 5, Table 8, and Table 10 interpret[13] the estimated L-V parameters for the first, second and third episode, respectively. Our estimated inter-powertrain relationships are depicted for all the three episodes in Table 6. In the followings, we present and explain our results for each episode.

Our estimation results for the period of 1985-1996 (Table 4) show that ICEV was estimated with the positive carrying capacity of 4.25E+02. This means that ICEV was developing in an environment which was moderately well-supplied with the new resources required for the further technological development of the powertrain (Table 5). The moderately favourable environment with the abundance of new resources made the powertrain as the most creative powertrain during 1985-1996 since it was estimated with the positive intrinsic knowledge growth rate of a=5.97E-01. This situation can be explained by the sharp decline in gasoline and diesel price in the 80s (Barbieri, 2016), and also by the earlier environmental regulations and standards[14] (Faria and Andersen, 2017b). These led to improvements in different components of the powertrain such as stoichiometric carburettor system, air fuel ratios, exhaust gas recirculation, crankcase and evaporative emission controls, electronic ignition timing, and fully electronic systems with fuel injection (Faiz et al., 1996). On the other hand, the intrinsic knowledge growth rate for both HEV and BEV was estimated to be negative, -1.06E+00 and -5.76E-01, respectively. This means that HEV and BEV were found to be moderately and slightly lacking knowledge creativity and variety in their technological system, respectively (see Table 5). This situation happens when the population of patents in a technological field exceeds the effective carrying capacity to an extent that the environment is no longer able to provide the required new resources for further knowledge development. This is why the effective carrying capacity of HEV and BEV was estimated to be negative (k=-5.54E+01 and -1.52E+02, respectively). The internal interaction rate for all the three powertrains was estimated to be positive, which means all the powertrains tended to act more like a knowledge exploiter than a knowledge explorer. We discovered HEV to be highly exploitative (b=1.91E-02), while both BEV and ICEV were found to be moderately exploitative (b=3.78E-03 and 1.41E-03, respectively).

	Parameters (t–value)						
	a_i	b_i	$k_i = a_i/\lvert b_i\rvert$	$C_{i,ICEV}$	$C_{i,HEV}$	$C_{i,BEV}$	R^2
ICEV	5.97E-01 (3.24E+00**)	1.41E-03 (1.39E+00*)	4.25E+02	- -	-4.88E-03 (-1.02E+00)	-3.02E-03 (-2.23E+00*)	0.9790
HEV	-1.06E+00 (1.34E+01***)	1.91E-02 (3.57E+01***)	-5.54E+01	-2.83E-03 (-3.09E+01***)	- -	-2.35E-03 (-6.78E+00***)	0.9970
BEV	-5.76E-01 (3.83E+00***)	3.78E-03 (2.31E+00**)	-1.52E+02	-2.27E-03 (-1.14E+01***)	9.29E-03 (4.28E+00***)	- -	0.9710

The estimation performance is good because all of the R^2 are greater than 0.85 (Kreng et al., 2012).
Notes: *, **, *** significant at p<0.1; p<0.05; p<0.01

Table 4- Results of parameters estimation for 1985-1996 'towards sustainable mobility'

	a_i	b_i	k_i
ICEV	Highly creative	Moderately exploitative	Moderately favourable environment with abundance of new resources
HEV	Moderately uncreative	Highly exploitative	Slightly unfavourable environment with deplete of new resources
BEV	Slightly uncreative	Moderately exploitative	Slightly unfavourable environment with deplete of new resources

Table 5- Parameters interpretation for 1985-1996 'towards sustainable mobility'

For the inter-powertrain relationship between BEV and HEV during 1985-1996, our estimation results show that, on the one side, HEV was benefiting from the knowledge growth in BEV, and on the other side, BEV's knowledge growth was inhibited by HEV (see Table 6). This kind of transaction made HEV as predator (C=-2.35E-03) and BEV as prey (C=9.29E-03) in a parasitic relationship. In this period, ICEV was found to be beneficial to the knowledge growth of both powertrains of HEV (C=-2.83E-03) and BEV (with C=-2.27E-03) vis-a-vis commensal and symbiotic relationships, respectively. In the symbiotic relationship with ICEV, BEV was estimated to have benefit the knowledge growth in ICEV with the external interaction rate of C=-3.02E-03.

Technologies	'Towards sustainable mobility' (1985-1996)	'Towards hybridisation' (1997-2007)	'Towards mass commercialisation' (2008-2016)

i	j	$C_{i,j}$	$C_{j,i}$	$C_{i,j}$	$C_{j,i}$	$C_{i,j}$	$C_{j,i}$
BEV	HEV	+	-	-	0	-	+
		Prey-predator		Commensalism		Predator-prey	
ICEV	BEV	-	-	0	+	+	0
		Symbiosis		Amensalism		Amensalism	
HEV	ICEV	-	0	-	0	-	-
		Commensalism		Commensalism		Symbiosis	

Notes: The value of those coefficients that were not found statistically significant was set to zero.

Table 6- Inter-powertrain relationship modes

Table 7 depicts our estimation results for the period of 1997-2007. The environment was estimated to become even more favourable for the ICEV powertrain in the second episode as it was teemed with further required new resources for its knowledge production (k=7.33E+02). The more favourable environment made the incumbent powertrain of ICEV even more creative in the industry as it acquired a higher intrinsic knowledge growth rate (a=6.89E-01). This observation can be confirmed by the findings of Borgstedt et al. (2017) that ICEV maintained its dominant position in the industry as it remained the core competency of the world's largest incumbent suppliers in the automotive industry e.g. Bosch, Denso, Continental and Hitachi. The environment for both HEV and BEV also became suitable as it shifted from being slightly unfavourable during the first episode towards slightly favourable during the second episode (Table 8). This is evident in the positive carrying capacity of both powertrains, 1.07E+01 for HEV and 1.05E+02 for BEV (Table 7). Unlike the first episode that HEV and BEV were found to be likely uncreative (Table 5), they shifted their orientation towards knowledge variety and creativity as they gained a positive endogenous knowledge growth rate in the favourable environment (a=3.74E-02 for HEV and a=3.83E-01 for BEV). The environment for BEV changed maybe mostly as a consequence of the establishment of some design and production networks in the mid-90's such as the 1993 partnership for a new generation of vehicles (PNGV) and the 1994 automotive research and technological development master plan, which accelerated the R&D activities in the field of BEV for the next few years (Sierzchula and Nemet, 2015). While HEV could in practice outcompete BEV with its higher range and performance, another reason significantly contributed to the knowledge growth of the powertrain. As a matter of fact, when the %2 BEV sales requirement for the years between 1998-2001 was eliminated from the ZEV mandate in 1996 (Wesseling et al., 2015), a few major automakers such as Toyota and Honda showed interest and involvement in the R&D and marketing activities for HEV (Oltra and Saint Jean, 2009). For example, the commercial introduction of the Toyota Prius I in 1997 was so successful in the Japanese green niche that more R&D and marketing activities were undertaken to launch the more advanced generation of hybrid vehicles in California, such as the 1998 Honda Insight and the 2000 Toyota Prius II (Dijk and Yarime, 2010). The high performance of the Toyota Prius II in California eventually convinced the California lawmakers to include HEV as a new category under the ZEV mandate in 2001. Since 2000 the R&D and marketing activities for HEV increased exponentially that the third generation of the Toyota Prius i.e. Prius III, was developed and launched worldwide in 2004 (Magnusson and Berggren, 2011).

The internal interaction rates estimated in Table 7 show that all the three powertrains continued their knowledge exploitive orientation in the industry. However, both ICEV and HEV powertrains became less knowledge exploitative compared with the first episode (b=9.41E-04 and b=3.51E-03, respectively). The knowledge exploitation behaviour of BEV did not change much as it continued to be moderately exploitative (b=3.64E-03) (Table 8). The estimated inter-powertrain relationships in Table 6 shows that the relationship between ICEV and HEV remained the same as HEV continued to benefit from the knowledge growth in ICEV vis-à-vis the commensal relationship. On the contrary, the inter-powertrain relationship between BEV and HEV and BEV and ICEV changed completely. The initial parasitic inter-powertrain relationship between BEV and HEV shifted towards commensalism in a way that BEV was no longer a prey to the predator HEV as it started benefiting from the hybrid powertrain's knowledge growth (C=-5.83E-03). Furthermore, the initial symbiotic relationship between ICEV and BEV shifted towards amensalism in which ICEV turned out to be inhibiting the knowledge growth in BEV (C=5.37E-04).

	Parameters (t–value)						
	a_i	b_i	k_i=a_i/|b_i|	$C_{i,ICEV}$	$C_{i,HEV}$	$C_{i,BEV}$	R^2
ICEV	6.89E-01 (3.01E+00**)	9.41E-04 (1.36E+00*)	7.33E+02	-	-3.03E-03 (-8.33E-01)	-2.48E-04 (-1.20E-01)	0.9040
HEV	3.74E-02 (5.97E+00***)	3.51E-03 (2.07E+00*)	1.07E+01	-4.24E-04 (-1.96E+00*)	-	-1.56E-03 (-1.26E+00)	0.9510
BEV	3.83E-01 (6.00E+00***)	3.64E-03 (2.62E+00**)	1.05E+02	5.37E-04 (1.83E+00*)	-5.83E-03 (-2.56E+00**)	-	0.9910

The estimation performance is good because all of the R^2 are greater than 0.85 (Kreng et al., 2012).
Notes: *, **, *** significant at p<0.1; p<0.05; p<0.01

Table 7- Results of parameters estimation for 1997-2007 'towards hybridisation'

	a_i	b_i	k_i
ICEV	Highly creative	Slightly exploitative	Highly favourable environment with abundance of new resources
HEV	Slightly creative	Moderately exploitative	Slightly favourable environment with abundance of new resources)

BEV	Moderately creative	Moderately exploitative	Slightly favourable environment with abundance of new resources)

Table 8- Parameters interpretation for 1997-2007 'towards hybridisation'

From the estimation results for 2008-2016 (Table 9 and 10) we observe that the environment during this period was found to have been likely unfavourable to all the three powertrains as their effective carrying capacity was estimated with negative values[15]. The environment was estimated to have been highly unfavourable to ICEV (k=-3.09E+03), slightly unfavourable to HEV (k=-5.61E+02), and moderately unfavourable to BEV (k=-1.59E+03). This implies that the population of patents in every single technological field have exceeded the corresponding effective carrying capacity to an extent which the environment could no longer provide the required new resources for knowledge development. Accordingly, the intrinsic knowledge growth rate of all the three powertrains was estimated with negative values. While ICEV and HEV were found to be moderately uncreative in the industry (a=-1.01E+00 and a=-9.83E-01, respectively), BEV was found to be more uncreative than the other two with a=-1.38E+00. Perhaps the environment turned out to be less unfavourable to HEV and BEV because of the emergence of some exogenous factors (events) in the industry shed more lights on the green vehicle economy, such as the 2005 fuel price soar, the emergence of the oil independent economy (Barbieri, 2016), the financial crisis of 2007 (Laperche et al., 2011), and the global awareness of environmental concerns (Hcec, 2005; Nielsen, 2007). For instance, a substantive amount of funding was allocated by the American Reinvestment and Recovery Act of 2009 to the office of Energy Efficiency and Renewable Energy (EERE) for the battery R&D in the U.S. (Public-Law-111-5, 2009). Nevertheless, the BEV powertrain still remained the core competency of smaller suppliers and firms whose main operations were outside the industry, such as Toyota Industries Corporation, LG Group, Toshiba, and Fuji Electric (Borgstedt et al., 2017; Faria and Andersen, 2017a).

In the likely unfavourable environment, ICEV continued its previous slightly exploitation strategy (b=3.26E-04), and while BEV became much less knowledge exploitative (b=8.68E-04), HEV shifted from being moderately exploitative towards moderately explorative (b=-1.75E-03). The inter-powertrain relationships estimated for the third episode (Table 6) show that the last relationship between BEV and HEV resembles the parasitic relationship during the first episode. The only difference in the parasitic relationship is that this time the position of the prey and the predator completely changed as BEV became the predator (c=-3.20E-03) and started benefiting from the knowledge growth in the prey powertrain of HEV (c=5.21E-04). Similarly, the direction in the ICEV-BEV amensalim relationship reversed as this time BEV started inhibiting the knowledge growth in ICEV (c=8.60E-04). While HEV continued benefiting from the knowledge growth in ICEV (c=-1.40E-04), their relationship shifted from commensalism to symbiosis as ICEV also started benefiting from the knowledge growth in HEV (c=-4.11E-03).

	Parameters (t–value)						
	a_i	b_i	k_i=a_i/|b_i|	$C_{i,ICEV}$	$C_{i,HEV}$	$C_{i,BEV}$	R^2
'Towards mass commercialisation' (2008-2016)							
ICEV	-1.01E+00	3.26E-04	-3.09E+03	-	-4.11E-03	8.60E-04	0.9060
	(3.35E+00***)	(1.79E+00*)		-	(-4.41E+00***)	(4.96E+00***)	
HEV	-9.83E-01	1.75E-03	-5.61E+02	-1.40E-04	-	5.21E-04	0.9760
	(6.13E+00***)	(-3.81E+00**)		(-2.06E+00*)	-	(5.70E+00***)	
BEV	-1.38E+00	8.68E-04	-1.59E+03	-7.70E-05	-3.20E-03	-	0.9850
	(7.52E+00***)	(1.43E+01***)		(-1.39E+00)	(-1.05E+01***)	-	

The estimation performance is good because all of the R^2 are greater than 0.85 (Kreng et al., 2012).
Notes: *, **, *** significant at p<0.1; p<0.05; p<0.01

Table 9- Results of parameters estimation for 2008-2016 'towards mass commercialisation'

	a_i	b_i	k_i
ICEV	Moderately uncreative	Slightly exploitative	Highly unfavourable environment with deplete of new resources)
HEV	Moderately uncreative	Moderately explorative	Slightly unfavourable environment with deplete of new resources
BEV	Highly uncreative	Slightly exploitative	Moderately unfavourable environment with deplete of new resources)

Table 10- Parameters interpretation for 2008-2016 'towards mass commercialisation'

5. Discussion and concluding remarks

We observe in the literature of conventional fields that the concept of competition between firms or technologies has been frequently used as the unit of analysis for explaining the evolution of technologies (Barney, 1991; Coccia and Watts, 2020; Fisher and Pry, 1971; Porter, 2008; Teece et al., 1997; Utterback, 1994). However, the interaction between technologies is not necessarily pure competition since the nature of any technological systems is to minimise negative effects as well as maximise positive effects in the market (Coccia, 2019b; Coccia and Watts, 2020). Technologies co-evolve vis-a-vis an evolution of reciprocal adaptations that may lead to different multi-mode interactions over time and space (Bryan et al., 2007; Coccia, 2017, 2019a,d; Geels, 2005; Raven and Verbong, 2007; Sandén and Hillman, 2011; Yang et al., 2019). In our study, we discovered a mix matrix of supportive and inhibitive forces that ended up in relationships other than pure competition, i.e. amensalism, parasitism, commensalism, and symbiosis. This supports our argument that the powertrain technologies are more likely to influence the knowledge growth of one another both positively and negatively in different periods.

The simultaneous presence of both positive and negative forces in our case nuances Schumpeter's gale of 'creative destruction' as well as the single-narrowing path forward view in which a disruptive technology outcompetes all the rivals by building an irreversible lock-in situation that makes the incumbent technology withdraw from the market (Schumpeter, 1934; Vergne and Durand, 2010). For example, we discovered that the two seemingly competing powertrains of ICEV and BEV benefitted from the knowledge growth of one another in a symbiotic relationship between 1985-1996. On the one hand, like most emerging technologies BEV benefited from a variety of factors provided by the first mover technologies like ICEV (Pistorius and Utterback, 1997), such as the distribution channel, market, educated customers, road and traffic infrastructure (Dijk, 2014; Dijk et al., 2015). On the other hand, the incumbent ICEV also started to benefit from the situation; first started accelerating improvements in its own technological components by noticing the emergence of BEV[16]; second it started borrowing some electric components from BEV for fuel efficiency (Dijk, 2014; Dijk et al., 2015). Such mutual benefits between competing technologies can be observed also among human beings in society since individuals occasionally display altruistic traits[17] by giving up their own resources to benefit the neighbourhood peers (Coccia, 2019b; Wenseleers, 2006). Therefore, the frequent existence of positive externalities in our case shows that the automotive industry has experienced a portfolio of multiple co-existing technological paths that may initially seem competing with one another for the same sources of ideas or knowledge domains but occasionally cooperate with one another by building spillovers of positive developments.

The strong evidence of the inter-powertrain positive and negative forces can be supported and explained by the concept of 'positive and negative externalities' in the technology management literature (Bergek and Onufrey, 2013; Onufrey and Bergek, 2015). A technology that possesses a positive or negative internal growth may project positive externalities or negative externalities in other surrounding technologies. This way positive or negative externalities are in fact the 'mirror effects' of the positive or negative internalities of the technology in the other technologies (Bergek and Onufrey, 2013). Positive externalities are evident in the three biological modes of symbiosis, commensalism, and parasitism (the positive side); while negative externalities are evident in the three modes of competition, amensalism, and parasitism (the negative side). Mirzadeh Phirouzabadi et al. (Unpublished results) argue that technological systems project as well as receive positive and negative externalities through their mutually coupled dynamics, e.g. *knowledge development co-dynamics*. Such co-dynamics can initiate knowledge spillovers from one system to another, which can lead to knowledge *overlaps* or *couplings* between the interacting systems (Noailly and Shestalova, 2017). The direction of knowledge spillovers (or externalities) generally depends on whether the interacting technological systems choose to acquire (or grant) knowledge during the interaction (Castiaux, 2007; Cerqueti et al., 2015; Mirzadeh Phirouzabadi et al., Unpublished results). The technological system that receives knowledge spillovers from the other systems possesses a negative external interaction value (negative C). Because the system generally opens up its knowledge perspectives mostly by bringing and exploiting the newness and knowledge variety from the other systems through actions such as collaboration with their organisations and customers, employment of their human capitals, or use of their artefact and patents (Castiaux, 2007). The technological systems that spill knowledge over to the system that receives it usually possess a positive external interaction value (positive C). This may be because the interaction has had a detrimental effect on the functioning of the systems through actions such as free riding, dismantling or weakening their knowledge networks, and altering their structures through acquisition and merger activities (Castiaux, 2007; Kivimaa and Kern, 2016; Mirzadeh Phirouzabadi et al., Unpublished results). These systems, hence, mostly focus on creating new knowledge endogenously through the creative orientation of internal individuals or actors, collaborative contacts between internal actors, learning from its customers, etc. (Castiaux, 2007). For example, the HEV-BEV parasitic relationship that we observed during the first period implies that there were some knowledge spillovers from the prey powertrain of BEV (with positive C) towards the predator powertrain of HEV (with negative C). The observed knowledge spillovers can be confirmed by the fact that the predator powertrain of HEV initially started borrowing and exploiting the knowledge domains that were originally developed for the components of the prey powertrain of BEV such as battery, charger, power convertor and controller, and traction and electric motor. For example, in the early 90's the Toyota hybrid system project team benefited enormously from the technological knowledge in the battery component that was already developed in cooperation with Mitsubishi for the BEV powertrain (Dijk, 2014; Köhler et al., 2013). Our results for the third episode, however, implies that the initial direction of the knowledge spillovers between the two interacting powertrains entirely changed from the first episode. While both powertrains maintained a parasitic relationship, this time the knowledge was being spilled over from the prey powertrain of HEV (with positive C) to the predator powertrain of BEV (with negative C). This may be because the predator powertrain of BEV has been able to not only exploit the effects of the economies of scale and learnings created by the prey powertrain of HEV for the shared components (i.e. battery, charger, power convertor and controller, and traction and electric motor), but also enjoy the positive social image and user acceptance created around the prey hybrid powertrain (Dijk, 2014).

The knowledge spillovers or externalities between the powertrain technologies exist because the knowledge domains produced for the development of a specific technology do not necessary exist for the sole development of the technology, but instead can be simultaneously embedded and exploited for several other technologies (Bergek et al., 2015; Mirzadeh Phirouzabadi et al., 2020a; Sandén and Hillman, 2011). This can be explained by the fact that knowledge is a multi-purpose good and can be indefinitely used and combined for different applications (Carnabuci, 2010; Mirzadeh Phirouzabadi et al., Unpublished results). This parallels the new growth theory that the knowledge domain growing around a technology (e.g. skills, tacit and codified knowledge) is driven by a recombinant of the existing knowledge domains around other technologies (Weitzman, 1996). Some studies argued and demonstrated that the actual or potential overlaps between technologies can be considered as a basis for the establishment of inter-technology relationships (Mirzadeh Phirouzabadi et al., 2020a; Mirzadeh Phirouzabadi et al., Unpublished results; Sandén and Hillman, 2011). In a biological ecosystem the various inter-population biological relationships occur because the populations actually or potentially have overlaps in terms of various resources such as air, food, and territory. Mirzadeh Phirouzabadi et al. (2020a), for instance, observed that the symbiotic and commensal relationships between HEV and BEV corresponded to the shared collaborations on the IPC classifications of B60K0006, B60L0011 and B60K0007[18]. Hence, in our case of powertrain technology, we can argue that the inter-powertrain biological relationships emanate from the actual or potential knowledge overlaps that are built between them over time vis-à-vis knowledge spillovers. Future studies can substantiate and elaborate the existence of potential or actual overlaps between technologies as a basis for their inter-technology relationships.

As observed in the previous section, the behaviour of the powertrain systems and the relationship mode between them go through temporal transitions from one episode to another.

We observed a shift from being creative (positive a) to uncreative (negative a), from being exploitive (positive b) to explorative (negative b), and from parasitism to commensalism and symbiosis (a mix of positive and negative values for the parameter C), or vice versa. The phenomenon of temporal behavioural changes and transitions can be related to both endogenous and exogenous factors (Coccia, 2019b; Markard and Hoffmann, 2016; Mirzadeh Phirouzabadi et al., Unpublished results; Pistorius and Utterback, 1997; Sandén and Hillman, 2011; Teece et al., 1997). We observed that the behaviour of the powertrain systems depended on whether the environment turned out to be favourable or unfavourable to them. A technological system might become more knowledge exploration oriented when there exists a net effect of internal and external economies of scale for the knowledge production in the system, such as declining of long-term average costs (Chiang and Wong, 2011). When the system senses a net effect of internal and external diseconomies of scale, it might stop exploring and building new knowledge and start exploiting the existing knowledge. In the case of BEV and HEV for instance, the temporal behavioural changes and transitions can be related to factors such as technical difficulties (e.g. limited ranges, and low performances), infrastructural unpreparedness (e.g. lack of maintenance and charging facilities), economical infeasibility (e.g. high costs), political (e.g. lobbying efforts by automobile and oil sectors) and market barriers (e.g. low demands and the need for high incentives such as direct subsidies, free parking, and CO2 and fuel taxes) (Dijk et al., 2013; Franke and Krems, 2013; Høyer, 2008; Prud'homme and Koning, 2012; Rudolph, 2016; She et al., 2017; Wesseling et al., 2014a). While future studies may look into the detailed reasons behind the temporal behavioural changes and transitions of the powertrain systems, any generic or specific behavioural patterns can be investigated and tracked down for forecasting purposes. For example, they may find the same spiral of exploration, exploration-to-exploitation, exploitation, and exploitation-to-exploration which was observed between two interacting organisations (Castiaux, 2007). Identifying the stability or instability state of a system can be instrumental to knowing the revival or demise of the system's intrinsic or interactive behaviour (Castiaux, 2007; Senge, 1997). These states can be determined by searching the equilibrium or tipping point in the L-V equations, where the time derivatives are equivalent to null (i.e. $dX/dt = 0$, $dY/dt = 0$, and $dZ/dt = 0$) (Castiaux, 2007; Choi et al., 2016). This point refers to a spot on the S-curve where the growth of a technology can accelerate dramatically and later sustain by only some insignificant changes (Phillips, 2007; Zeppini et al., 2014).

The results of our research can inform the decisions of those managers and policy makers who want to know when to invest in the R&D of new disruptive technologies by offensive strategies; when to sustain the incumbent technology by defensive strategies; and when to pursue a hybridised technology as a transitionary option by intermediate strategies (Coccia and Watts, 2020; Utterback et al., 2018). The mix matrix of supportive and inhibitive forces (or positive and negative externalities) informs policy makers and managers that their policy mixes can generate not only positive or negative internalities for the intended powertrain technology, but also positive and negative externalities in the field of other powertrain technologies. This is because innovation policy mixes can possess the dual role of *creation* and *destruction* in the industry (Kivimaa and Kern, 2016). An innovation strategy may, hence, turn out as the two sides of a coin. It may be initially formulated to lead to the creation of a technology, but at the same time, it may lead to the destabilization of another neighbourhood technology (Mirzadeh Phirouzabadi et al., 2020a). The phenomenon of multi-modal interaction also recommends that the innovation strategy dedicated to a specific technology will be not necessarily unitary and should not be formulated in isolation from other technologies. This situation can be observed in the lawsuit action which was filed by the major automakers against the CARB's ZEV mandate in 2002. While the major automakers forced the policy makers to include the new but less promising powertrain of fuel cell vehicles (FCV)[19] in the ZEV mandate (Nrdc et al., 2008; Wesseling et al., 2015), their action eventually led to the destabilization of the BEV powertrain situation that happened to be a more mature and promising technology at the time (Mirzadeh Phirouzabadi et al., Unpublished results). We recommend that policy makers and managers formulate an innovation strategy devised for a relationship mode between two interacting technologies differently from an innovation strategy devised for another relationship mode between them. For instance, a symbiosis strategy should be differently formulated from a pure competition or parasitism strategy. A typical symbiosis strategy should be formulated in a way that would aim at supporting the growth of the two interacting technologies, while a parasitism strategy should aim at supporting the growth of one technology and inhibiting the other (Utterback et al., 2018). Additionally, the temporal inter-powertrain relationship transition in our case study recommends them not only to devise and deploy specific (offensive or defensive) strategies for each of the interaction modes but also to change their strategies in accordance with the transition between the modes (Pistorius and Utterback, 1997; Utterback et al., 2018). If policy makers and managers perceive a temporal transition from symbiosis to parasitism among two interacting technologies, the nature of strategy should accordingly shift from symbiosis to parasitism. Selection of a wrong strategy for a particular mode can be catastrophic and irreversible (Utterback et al., 2018). Such an understanding is crucial in the area of sustainability transition in which the goal is escaping from dysfunctional locked-in systems while fostering better long-term prospects and avoiding dead ends (Sandén and Hillman, 2011).

Finally, future studies may wish to investigate the inter-powertrain relationships with the inclusion of intra-component interactions within individual powertrain systems. Based on technology definition (Coccia, 2019b,c; Simon, 1991), the evolution of a powertrain system not only involves the inter-systems relationships (i.e. the linkage with the other powertrain systems) but also the intra-component relationships (i.e. the linkages between its own component and sub-component). We considered each powertrain system as a whole (single entity) without going into details for the intra-component relationships. For example, the powertrain system of BEV itself is comprised of several components such as battery, charger, power convertor and controller, and traction motor which are not isolated from one another, but rather interact with one another as parts of the overall design (Mcnerney et al., 2011). This can be significant as the behaviour and evolution of a technological system is internally associated with the behaviour and evolution of its own components (Coccia, 2019b; Coccia and Watts, 2020; Mcnerney et al., 2011; Zhang et al., 2019c). The theory of host and parasite technologies (Coccia, 2019d) can be applied here as it for example considers the BEV system as the host technology (platform) and the internal connecting components as parasite technologies. This way we can investigate both the trickle-up effect (the effect from system level to component level) and trickle-down effect (vice versa) within technological systems (Zhang et al., 2019b; Zhang et al., 2019c). With the identification of the most effective and significant components in each technological system, policy makers and managers can discover not only which components need more incentives and regulations for accelerating the evolution of the systems as a whole, but also which components should be invested and designed in-house or outsourced and purchased from outside (Zhang et al., 2019a).

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Appendix A

Search terms of keywords and IPC codes (Mirzadeh Phirouzabadi et al., 2020a; Mirzadeh Phirouzabadi et al., 2020b)

Technological field	Search query
ICEV-related patents	TAB=(("internal combustion engine" OR "ic engine" OR "diesel engine") AND (vehicle* or car or automobile*)) AND (PRDS>=(19850101) AND PRDS<=(20161231)) AND IC=(F01* OR B60* OR F02B* OR F02D* OR F02F* OR F02M* OR F02N* OR F02P*);
HEV-related patents	TAB=("hybrid electric vehicle" OR "hybrid vehicle" OR "hybrid propulsion" OR "hybrid car" OR "hybrid automobile" OR "hybrid electric car") AND (PRDS>=(19850101) AND PRDS<=(20161230)) AND IC=(F02* OR F16H* OR B60K006* OR B60W020 OR B60L00071* OR B60L000720)
BEV-related patents	TAB=(("electric vehicle" OR "electric car" OR "electric automobile") AND battery AND (vehicle* or car or automobile*)) AND (PRDS>=(19850101) AND PRDS<=(20161230)) AND IC=(H02k* OR H01M* OR B60L011* OR B60L003* OR B60L015* OR B60K00101* OR B60W001008 OR B60W001024 OR B60W001026)

The asterisk wildcard (*) represents zero or an unlimited number of characters. For instance, vehicle* also includes results containing vehicles, or B60K006* also includes results containing B60K00620, B60K00646, and so on.

Appendix B

Descriptive statistics of the patents data for each powertrain technology

		BEV	HEV	ICEV
N	Valid	32	32	32
	Missing	0	0	0
Mean		584.0625	340.25	1536.0625
Std. Error of Mean		132.61413	58.9137	186.02093
Median		261	243.5	1282.5
Mode		1.00a	1	318.00a
Std. Deviation		750.17881	333.26624	1052.29332
Variance		562768.254	111066.387	1107321.22
Skewness		1.563	0.693	0.479
Std. Error of Skewness		0.414	0.414	0.414
Kurtosis		1.31	-0.77	-1.246
Std. Error of Kurtosis		0.809	0.809	0.809
Range		2507	1018	3088
Minimum		1	1	318
Maximum		2508	1019	3406
Sum		18690	10888	49154

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[1] Note that like several recent studies (Borgstedt et al., 2017; Faria and Andersen, 2017b; Mirzadeh Phirouzabadi et al., 2020a; Oltra and Saint Jean, 2009) we did not specifically include the plug-in HEV powertrain (PHEV) in our research.

[2] Technology—the collection of devices and methods available to human society—evolves by constructing new devices and methods from ones that previously exist, and in turn offering these as possible components—building blocks—for the construction of further new devices and elements. The collective of technology in this

way forms a network of elements where novel elements are created from existing ones and where more complicated elements evolve from simpler ones (Arthur and Polak, 2006, p23).

[3] There are generally seven dynamics in a TIS: knowledge development, knowledge diffusion, entrepreneurial activities, guidance of search, resource mobilization, market formation and creation of legitimacy. And when a dynamic from a TIS becomes coupled with the same dynamic in another TIS, a co-dynamic is shaped between them. Since the focus in our research is studying multi-technology interactions in terms of knowledge growth and development, we only investigate knowledge development dynamics and co-dynamics. This is simply because conceptualising as well as quantifying all the seven dynamics and co-dynamics of technologies is beyond the scope and space of a single article.

[4] This included *Automotive News, WardsAuto World*, *Autoweek*, *Financial Times* (Bohnsack et al., 2015).

[5] Wherever we mention patent(s) in this study, we mean patent family(ies). For detailed justification, see Borgstedt et al. (2017).

[6] The priority date of a patent is known as the closest date to the submission of the invention (Barbieri, 2016).

[7] "A patent is valid if the claim contains the categorized technology as well as the possibility of an automotive utilization" (Borgstedt et al., 2017, p79).

[8] For mathematical details, refer to Porter et al. (1991: p. 191).

[9] The carrying capacity of a biological species in an environment is generally understood as the maximum population size that the environment can sustain the species indefinitely, given the food, habitat, water and other necessities available in the environment (Yukalov et al., 2012). So, by definition, 'k' can determine only the maximum population size not the actual population size. It may however be used to calculate the difference between the actual population size and the maximum population size. 'k' starts declining when the environment (and the resources that it provides) becomes unfavourable (or seldom) to the species. 'k' can decline so much that it can gain a negative value. In some studies, when they found a negative value for carrying capacity, they assumed 'k' is zero (Gabriel et al., 2005), meaning the environment can only support zero population. Like some other studies (Yukalov et al., 2012), we however kept negative values and did not change the values to zero to emphasize how extremely unfavourable the environment has become for the population. The negative carrying capacity refers either to the complete depletion of resources required to meet the needs of the population, or to the accumulation of too much of their wastes that will poison the population eventually, or to both (Advani et al., 2018; Hui, 2006). And Since the environment will no longer be able to provide the required resources not only for the birth of their new offspring but also for the current situation of the existing ones, the

population will start declining in numbers with a negative endogenous growth. The explanation for the existence of a negative carrying capacity becomes even more transparent when the unit of analysis is technological or economic systems. The negative carrying capacity of a system can not only refer to the depletion of the required resources for the system (for example humans over-extracting the renewable and non-renewable resources), but also to the borrowed resources that need to be returned back to the lender—assuming that there is a maximum level of debt, beyond which the system highly loses its stability due to feedbacks resulting from market forces (Yukalov et al., 2012).

[10] While ‘k’ is calculated using the parameters ‘a’ and ‘b’, and ‘a’ and ‘k’ will always have the same sign in our analysis since k= a/|b|, it does not necessarily mean that ‘a’ and ‘b’ are responsible for the resource provision in the environment. The environment with infinite, renewable resources can set unlimited maximum population level for a population, on the one hand, and the same environment can bring unfavorable circumstances for the same population through catastrophic events or accommodating other new entrants that the population would face a dead-end, on the other hand. Parameters ‘a’ and ‘b’ are only determining at what speed the resources provided by the environment are being consumed. Hence, ‘k’ can be used to imply if the environment is favourable to a population or not (Advani et al., 2018; Hui, 2006).

[11] Since we initially and mainly selected the cut points in our research based on major industry events, the cut points used in the literature (Faria and Andersen, 2017a; Faria and Andersen, 2017b; Mirzadeh Phirouzabadi et al., 2020a; Mirzadeh Phirouzabadi et al., 2020b), and the trend of our raw data, a robustness check was completed to see how the value of parameters change if we select different cut points. To do so, we selected the first episode (1985-1996) as it contains the most influential technology forcing event in the middle, i.e. the California 1990 ZEV Mandate. We halved the first episode into two sub-episodes: the first half 1985-1990 (before the Mandate) and the second half 1991-1996 (after the Mandate). We then performed an intra-episode comparison by estimating and comparing the value of parameters ‘a’, ‘b’, ‘k’, and ‘c’ for each sub-episode. The results showed that the value of parameters not only changed slightly from 1985-1990 to 1991-1996, but also remained relatively close to the results for the entire episode (1985-1996). Apart from the intra-episode comparison, we also did an inter-episode comparison. We halved the second episode 1997-2007 into two sub-episodes 1997-2002 and 2003-2007, and then compared the results of the second half of the first episode 1991-1996 with the results of the first half of the second episode 1997-2002. Unlike the intra-episode comparison findings, we observed that the value of parameters shifted remarkably from 1991-1996 to 1997-2002. The value of some parameters shifted so much that their sign changed from positive to negative and vice versa. Our intra

and inter-episode comparison findings demonstrate that the values of parameters vary slightly when two segments are taken and compared from the same episode while they vary drastically when two segments are taken and compared from two different episodes. Although this robustness check demonstrates our appropriate selection of cut points mainly for the first episode, other different cut points can be taken and compared for stronger robustness by future studies.

[12] Descriptive statistics such as mean, SD, skewness and kurtosis is exhibited for the patents data of each powertrain technology in Appendix B.

[13] All the thresholds 'slightly/moderately/highly' are relative to other time periods included in the analysis instead of an absolute extent. We determined the threshold points for a parameter first by calculating the minimum, maximum, mean (μ=sum/n), and standard deviation (σ=(max-min)/6) for the range of values estimated for the parameter, and then forming the normal distribution chart using μ, $\mu\pm\sigma$, $\mu\pm2\sigma$, and $\mu\pm3\sigma$. Note that since interpretation for the positive values of a parameter is different from interpretation for its negative values, we measured threshold points for the positive values separately from threshold points for the negative values. For instance, for the four positive values estimated for the parameter 'a' during all the three episodes, the threshold points were set as follows: slightly creative if $a =< \mu-\sigma$; moderately creative if $\mu-\sigma < a < \mu+\sigma$; and highly creative if $a >= \mu+\sigma$.

[14] Some of the main standards and regulations in the U.S. were the 1970 Clean Air Act and its amendments in the 70s, 80s, and 1990, and the 1989 Low Emission Vehicles (LEV) program and its amendments in 90s and 2000s. Elsewhere around the world, especially the EU countries adopted the U.S. vehicle emission standards under various titles such as ECE 15 in 1970, amended several times in 1974, 1977, 1979, 1981, 1984 and 1986, ECE 83 in 1988, 91/441/EEC in 1991, and 94/12/ECE in 1994. Other countries, such as Argentina, Australia, Brazil, and Canada started following the same standards and requirements as of early 1995 (Faiz et al., 1996).

[15] This is worth mentioning that we obtained negative values for the carrying capacity as well as the intrinsic growth rate of all the powertrains in the last episode because the number of patents of all the three powertrains was decreasing since 2013 (Figure 1a). Two reasons could exist when the number of patents in a technological field declines at the end of observation period. First, the lower number of patents could be due to less innovative activities or collaborations in the technological field. Second the patent database could not include those patents accepted after the completion of the sample due to the long timespan between the application and publication of a patent (Borgstedt et al., 2017). The second reason could be more plausible for the case of powertrain technologies since the R&D activities at least for BEV and HEV must have increased in the last decade,

especially once the most stringent sales requirements of ZEV were set in 2012 for the model years 2018-2025. Solving the patent pendency, however, is inevitable for a timely analysis (Borgstedt et al., 2017; Mirzadeh Phirouzabadi et al., 2020a).

[16] The huge improvement reaction that the incumbent ICEV powertrain projected after the emergence of the BEV powertrain is known as 'sailing ship effect' in innovation studies (Sick et al., 2016). The concept originally refers to the innovation efforts that the incumbent sailing ships gained after noticing the introduction of the newly developed steam ships in the 19th century (Gilfillan, 1935).

[17] While such altruistic traits conflict with the Darwinian theory of natural selection as they may temporarily and to some extent lower the reproductive fitness of individuals, there are ample evidences of cooperation between potentially competing entities in both natural and social systems (Coccia, 2019b).

[18] These IPC classifications are related to the arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, battery development, electric motors and dynamo-electric machines.

[19] We did not include the FCV powertrain in our research due to time and space restriction. This did not, however, affect our results as we reached a high estimation performance. Future studies can include and specify the other powertrains such as FCV and PHEV to perfect the analysis.