Model-based approaches for technology planning and roadmapping: Technology forecasting and game-theoretic modeling

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A B S T R A C T

This paper proposes a novel model-based approach to technology planning and roadmapping, consisting of two complementary steps: technology forecasting and game-theoretic planning. The inherent uncertainty of target technology performances, timelines and risks impact the roadmapping process. Reducing this uncertainty is a major challenge and allows elaborating different options and scenarios. A formal methodology is proposed for quantitative forecasting in a multi-dimensional space (different performance metrics and time) based on past technology development trend information. The method adopts concepts and approaches from econometrics and is formulated as a convex optimization problem with different constraints on the frontier's shape. It provides useful product line assessment benchmarks and helps to set reasonable goals for future technology developments.

Game-theoretic planning allows addressing the strategic decisions to take, considering the technology landscape, markets, and competition. The strategic decisions affect in turn other companies as well, which is the basis for the application of game theory, in the form of best-response functions to determine the subsequent reactions and movements of rivals in a technological landscape. The result is a simulation of a sequential game in technology space, allowing evaluating possible technological development pathways and determining optimal models on the Pareto frontiers, potential targets for technology roadmapping.

1. Introduction

Pursuing the goal of surviving in rapidly changing environments, technology companies resort to numerous techniques to plan their technology investments and define a technology strategy. Due to the increasing role of technology strategy in driving profitability of business operations, and due to the increasing complexity and interdependencies between technologies and products, *Technology Planning and Roadmapping* (TPR) has become over the years an essential corporate function in large technology organizations. TPR approaches vary in scope and format. Technology roadmapping is used to produce visual displays of information from market, product and technology perspectives for external communication purposes. In its most advanced implementations, technology roadmapping is implemented to define multi-layered time-based roadmaps providing focus and integrating technology developments into future products and services, within organization's top-down vision and strategy (Phaal et al., 2009, 2004). To accomplish these goals, technology roadmaps incorporate inputs across the entire organization including R&T, engineering, product policy, corporate strategy, support functions and outside partners – such as suppliers – while keeping track of developments of other relevant external entities.

A McKinsey study (Heim et al., 2017) highlights that existing roadmapping solutions fail at identifying "white spots" in technology development. They also fail at offering a holistic view on how technologies and markets may evolve over time, and what such changes may imply for future products. Therefore, companies face several challenges in planning technology and building a technology roadmap:

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- *the moving-target dilemma ("How will technology markets change in the future?"),*

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- *the resource-focus dilemma ("Which of the multiple options should limited resources be allocated to?"), and*
- *the evolution-revolution dilemma ("What should be emphasized: incremental or breakthrough innovations in a technology portfolio?").*

>> (Heim et al., 2017)

Selecting a technology roadmap restrains an outcome to a certain tradespace region with limited evolution and demands of demonstrating a technology or raising the Technology Readiness Level (Mankins, 2009). In a case of technology demonstration failure or other exogenous changes, an anticipated architecture and its magnitude of development would be restricted (Davison et al., 2015). We assert that a preliminary analysis of the technology tradespace and its possible evolutions, key competitors and associated technology targets, is needed to support the choice and mitigate financial uncertainties. The goal of this paper is to propose a novel approach for technology roadmapping and planning, to support technology experts and decision-makers in the process of R&D planning and selection, through quantitative, model-based approaches, and rigorous mathematical models of technology evolution.

This paper models technological progress as quantitative forecasting of technology over time across key Figures of Merit (FOM) such as performance, cost, and risk (Yuskevich et al., 2018a), and the interplay of strategic decision-making in technology investments in a firm as a function of potential technology investments undertaken by competitors (Smirnova et al., 2018). The paper integrates two mathematical approaches: Pareto frontiers for technology forecasting and game theory for technology planning. The resulting framework represents a technology planning process as an extensive-form game. The Pareto-forecasting approach identifies Pareto optimal designs forecasted into the future (Yuskevich et al., 2018a). The game-theoretic approach simulates strategic industry competition among key producers through modeling of sequential games (Smirnova et al., 2018). This paper extends previous work by the authors (Smirnova et al., 2018; Yuskevich et al., 2018a) by providing a multi-dimensional formulation of the framework for $N > 2$ figures of merit and $N > 2$ number of producers within one technology tradespace. The framework is applied to a case study of future automobile conceptual design.

The remainder of this paper is structured as follows. Section 2 provides background information on related research. Section 3 defines a comprehensive description of the framework for N players, illustrated with a notional three-player example. In addition, this section provides a discussion of challenges and limitations of the approach. Section 4 presents the application of the proposed approach on an automotive industry case study. Section 5 discusses the validation of the proposed approach. Section 6 provides conclusions and lays out avenues for future work in technology forecasting and planning.

2. Literature review

In order to provide theoretical context to the work presented in this paper, this section overviews previous research in technology planning and roadmapping, with particular emphasis on multi-dimensional Pareto frontier forecasting and game-theoretic planning.

2.1. Multi-dimensional Pareto frontier forecasting

According to Phaal et al. (2004), the key defining feature of a technology roadmap is a time-based layered structure often visualized in a form of a chart. In his approach, the decomposition in levels (usually technology-product-market) helps to formalize technology/system requirements and market expectations and explore the relationships between them.

In the context of roadmapping for complex technical systems, technology levels are of the particular interest. Consequently, technology assessment (TA) and technology forecasting (TF) are important components in technology roadmapping. In the roadmap architecture recently proposed in Knoll et al. (2018) a special role is given to Figures of Merit (FoMs), the quantitative performance indicators used to assess competing technologies, components, systems, products and services. The process of building high-quality roadmaps requires tools for accurate forecasting of future FoMs.

Due to the fact that roadmapping activities are often focused on emergent technologies, products and services, the authors usually suggest using forecasting methods based on qualitative approaches such as expert opinions (Bloem da Silveira Junior et al., 2018), bibliometrics (Bildosola et al., 2017; Kostoff and Schaller, 2001; Martin and Daim, 2012) and patent analysis. The widespread use of expert elicitation is also due to the traditional approach of developing roadmaps through workshops (Phaal et al., 2004). Quantitative methods such as model-based approaches have not traditionally been employed in technology planning and roadmapping.

Although the use of quantitative approaches received relatively little attention in the literature, previous work has demonstrated the application of quantitative trend extrapolation methods to forecasting incremental technology evolution at all levels of the value chain (technologies, components, systems) (Anderson et al., 2002; Iamratanakul et al., 2005; Inman et al., 2006). Quantitative technology forecasting becomes relevant as soon as sufficient information about existing systems is gathered and organized in structured databases. Such information, which typically refers to incremental evolution of technology, can also be used to estimate the likelihood of “technology jumps” in terms of technology disruption. Incremental technology progress may eventually lead to disruptive technology jumps, and therefore emergence of completely new products and services. For instance, the gradual miniaturization of electronics enabled the integration of digital cameras into smartphones with an emergence of all corresponding services. Incremental progress can also lead to a rapid adoption of new technology and consequent turbulence on the market. According to disruptive innovation theory, the latter happens when a new technology breaks the low-end performance demand (Christensen, 1993). This strategy is referred to as low-end disruption. On the other hand, some companies may pursue a high-end disruption strategy aiming at gradual affordability improvement by investing in high-performant technologies. An example of a company implementing such a strategy is Tesla Inc. (Dyer and Furr, 2015). In the context of disruptive innovation planning, quantitative trend extrapolation approaches can be used for time predictions to estimate time of adoption of a technology of interest.

Usually, disruption theories are illustrated with charts of state-of-the-art performance (or affordability) and performance (or affordability) as demanded by different market segments versus time (Christensen, 1993). The real picture, however, is multi-dimensional (Fig. 1).

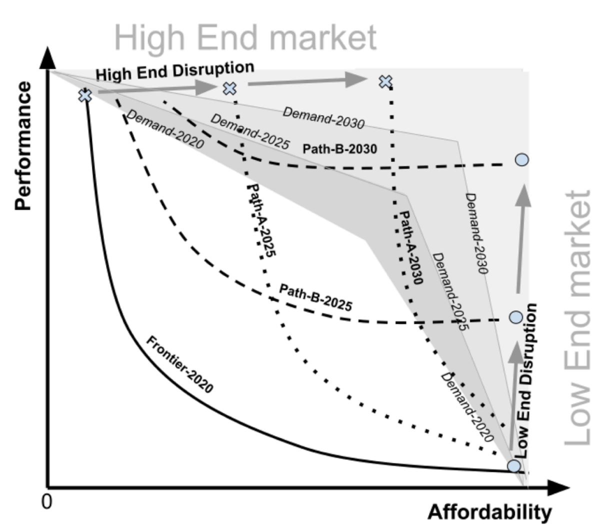


Fig. 1. Multi-dimensional illustration for the disruptive innovation strategies.

A company may choose to invest into high-end regions of the technology frontier to improve affordability (path-A), or into the low-end region to improve performance (path-B); they also can opt to pursue both performance and affordability improvement in different proportions. For instance, the aforementioned case of Tesla Inc. (Dyer and Furr, 2015) indicates that their technology investments aimed not only at the development of more affordable car models, but also at better performance, such as by improving battery capacity.

By integrating with Disruptive Innovation Theory (DIT) (Christensen, 1993), quantitative approaches can also be used to forecast the emergence of disruptive technologies, by estimating the cross-over time at which incremental evolution of technology breaks the so-called Low-End performance thresholds, as defined in DIT. For instance, the emergence of smartphones in the retail market could be forecasted by looking at the gradual miniaturization of electronics and correspondingly the integration of digital cameras into phones.

Trend extrapolation is a numerical method of particular interest in technology forecasting. Extrapolation allows inferring future evolution of technology as a function of prior evolution. Trend extrapolation is implemented by combining different forecasting approaches. For example, Martin and Daim (2012) discuss the combination of multiple forecasting approaches (e.g., bibliometrics, patent analysis, Delphi, technology intelligence, etc.) within the roadmapping process to overcome limitations of a single technique and enrich the results of the analysis. Technology forecasting can be performed by looking at evolution on individual or multiple figures of merit. Multidimensional Technology Forecasting (TF) was initially proposed by a research group from Portland State University. In their initial work (Anderson et al., 2002), TF is approached using Data Envelopment Analysis (TFDEA). The idea of TFDEA is to assess existing technical systems by calculating efficiency scores using DEA and making forecasts by estimating technology rates-of-change. This approach was validated successfully in application to performance prediction for microprocessors (Anderson et al., 2002), computer display projectors (Iamratanakul et al., 2005), jet fighter aircrafts (Inman et al., 2006), wireless networks (Anderson et al., 2008), passenger airplanes technologies (Lamb et al., 2010) and electric vehicles (Jahromi et al., 2013). In Lim and Anderson (2016) the evolution paths of the flat panels technologies were built, and results discussed through the lens of Disruptive Innovation Theory. DEA models assume of convex production sets. Forecasting using DEA, therefore, imposes the constraints on the shape of the Pareto frontier composed by the Figures of Merit of interest. Nevertheless, the literature shows that the assumption of convexity is quite strict and is often not respected in engineering applications. As an example, Smaling and Weck (2007) showed that the number of design options based on several different design concepts mapped in the same multi-objective criteria space form a non-convex feasibility set. A theoretical evolution of interest is, therefore, to extend DEA to non-convex Pareto frontier shapes. Previous work in (Yuskevich et al., 2018a) by the authors of this paper has proposed such evolution, framing technology evolution as a multivariate extrapolation of scattered data. Compared to TFDEA, the approach in (Yuskevich et al., 2018a, 2018b) enables the estimation of both increasing and decreasing returns-to-scale frontiers and adopts growth-curves models as proven patterns of technology performances evolution and infusion rates in a single run of the linear optimization procedure. The paper extends this previous work to a general, n-dimensional formulation of the problem.

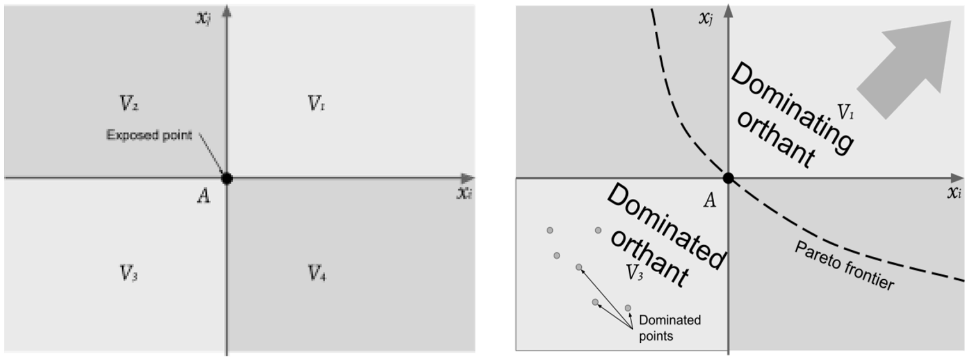
2.2. *Game-theoretic technology planning*

Game theory is widely used to study economic, political, and biological phenomena (Osborne, 2003). The application of game-theoretic approaches in engineering design and, especially, system engineering is a topic of interest in engineering research. Its application in the engineering field has been historically limited to the study of interactions between designers in selection and design of complex systems. The theoretical and mathematical basis of games is used to abstract the processes required to design a complex system.

In Vincent (1983) it is shown the usefulness of some of the game-theoretic concepts in engineering design, through the analysis of a generic mathematical problem in engineering. The authors mention the application of game theory to model decentralized design by a team of engineering designers. A number of studies have followed this topic. For instance, Chanron and Lewis (2005) modeled a design process where decision makers follow an iterative process of communication and developed the vector, scalarization, and trade-off-curve methods to achieve multi-objective solutions. A different framework (Smirnov at al., 2019) was proposed for design optimization using game theory, where a design process with any number of discipline designers is shown as a normal form game. This work describes the difference between Nash Equilibria and Pareto optimal solutions. In Brafman et al. (2009), a Coalition-Planning game formulation has been developed for self-interested players with personal goals who find the cooperation with each other beneficial in order to increase their personal net benefit. The research is focused on cooperative self-interested agents in groups (Hadad et al., 2013) and game scenarios in resource coalition (Dunne et al., 2010). A pure game-theoretic approach has been proposed to perform a strategic analysis of all possible player strategies and define equilibria based on the relationships between different solutions in game-theoretic terms (Bowling et al., 2003). Another work (Jordán and Onaindia, 2015) used the game-theoretic approach for non-cooperative planning to predict the plan schedules which player will adopt so that the set of strategies of all players constitute Nash Equilibrium (NE). Similar research (Davison et al., 2015) has been devoted to defining and plotting 'evolution' pathways within a tradespace in the form of the weighted directed graph where nodes are possible architectures. In Goswami et al. (2016); Sadeghi et al. (2011), product portfolio management is considered as a combinatorial optimization problem for a competitive duopolistic market. The focus of Goswami et al. (2016) is to develop a Bayesian-Game theoretic framework for planning problem thereby aiding the manufacturers operating across the variety of product industries to offer the right product portfolio set. Initially, feasible product portfolio candidates are generated as combinations of different product attributes and their attribute levels employing the attribute compatibility constraints. Manufacturing costs and product premiums, respectively, are estimated for different product portfolios, employing function-based cost-estimating relationships and multi-linear regression methodology. A Bayesian approach is used to classify purchase probabilities in high, medium and low-risk states for various product portfolios. The purchase probabilities so obtained act as input to the final payoff calculation. Finally, employing these payoff values, product offering scenarios are populated for the two manufacturers both in equilibrium and non-equilibrium state.

A development planning approach using game theory and network model was suggested in Xiong et al. (2017) to address the strategy selection and evolution of weapons systems-of-systems (WSoS) characterized by a competition between countries. With the development of weapons, SoS planning is changing in a state whereby every country is chasing each other especially potential competitors. The development planning framework includes a game player, strategy definition, and constraints (e.g., time and money). The framework defines a combat network presenting a structure and evolution of WSoS. Next, the selection process of the development planning strategy is considered based on damage accumulation and mitigation related to WSoS confrontation. Finally, a competitive coevolution algorithm is designed to find the optimal development strategy, reflecting that WSoS evolve along with the strategy selection change.

Choosing a promising project with desirable outcomes is an important stage of technology planning. The correct choices of roadmap and technology development (e.g. R&D projects to perform) influence an enterprise's successful position at the market. They are essential for a firm's competitive advantage and long-term goals. Failures in



(a) (b)

Fig. 2. Two-dimensional objective (criteria) space.

technology investment decision-making have ripple effects in an organization bottom line for years, and may lead to significant waste in research and development resources. The work of Heidenberger and Stummer (1999) gives an overview of quantitative methods for selecting R&D projects and allocating resources. They describe game theory approaches as those explicitly considering rational acting of a firm's environment which depends on the firm's actions. However, a gap is observed between the complexity of real-life decision-making and its corresponding theory. Heidenberger and Stummer (1999) exemplify the game-theoretic approach by considering a patent race in a duopolistic market; dynamic aspects of R&D competition and a framework for assessing a value of intermediate result in R&D project under competition. This paper builds on the state of the art here presented and generalizes the forecasting and strategic planning approach to a case of a market with multiple players.

3. Methodology

Building on the literature reviewed in Section 2, this section describes a methodology to technology planning and roadmapping based on multi-dimensional Pareto frontier forecasting and game-theoretic planning (considering scenarios with n firms operating in the market).

3.1. Multi-dimensional Pareto frontier forecasting

The feasibility boundary of technology performance can be numerically modeled as a surface in the n-dimensional space defined by the FoMs of interest. The evolution of technology can be modeled as the time-variant extension of the FoM surface:

$$F(X, t) = 0, \tag{1}$$

Where $X = (x_1, x_2, \ldots, x_n)$ are quantitative (performance, cost, etc., $x_i \in R$) and categorical (e.g. features, functions, etc., $x_i \in N$) FoMs of a technology or a system, whereby the concrete value of vector X is the Pareto-optimal combination of characteristics at the time t (state-of-the-art).

Each quantitative element within vector X following production efficiency theory (Farrell, 1957) can be classified as inputs or outputs. System designers typically aim at minimizing inputs (such cost, consumption, mass, etc.) and maximizing outputs (performance, reliability, user experience, value, etc.) in order to obtain efficient and competitive designs. Additionally, each element of vector X may have lower X_l and upper bounds X_u (physical limits). In each specific case physical limits shall be estimated beforehand. For example, generally energy conversion efficiency lies between 0 and 1, but maximal Carnot efficiency of specific heat engine depends on the ratio of working temperatures and usually does not exceed 0.5.

To explain the mathematics involved in the proposed methodology, three notions need to be introduced from convex geometry: convex set, exposed points and orthants.

By definition, a convex set C is a set of points such that, given any two points A, B in that set, the line AB joining them lies entirely within that set. An orthant in n-dimensions can be considered as the intersection of n mutually orthogonal half-spaces (thus orthant is a convex set). An orthant in 2-dimensional space is called a quadrant.

In Fig. 2a, point A divides a two-dimensional space into four convex sets (quadrants): $V_1,\ V_2,\ V_3,\ V_4$. In mathematics, the exposed point A of a convex set V is defined as the point $A \in V$ in which a linear function attains maximum value over V. If $x_i,\ x_j$ are both outputs, then function $\varphi(X) = x_i + x_j$ exposes A over V_3. All points belonging to V_3 are referred to as *Pareto dominated* by A and points belonging to V_1 are *Pareto dominating* for A (Fig. 2b).

Depending on the type of FoM (input or output) (mathematically defined by a form of the function $\varphi = \sum_{i=1}^{n} (\pm 1) \cdot x_i$), each point in $\mathbb{R}^n$ will be exposed by φ over just one convex set (orthant) out of 2^npossible. An orthant for which A is an exposed point is of particular interest. We further refer to this orthant as dominated and denote $V_{dom}(A)$ and the opposite orthant (for which functional$\varphi_{inf}(X) = -\varphi_{dom}(A)$) as a dominating orthant $V_{inf}(A)$.

The input for the forecasting algorithm is a set of scattered observations that are known from the past evolution of technology $S = \{(X_1, t_1),\ (X_2, t_2) \ldots\ (X_m, t_m)\}$. The problem of trend extrapolation consists in finding the one-sided interpolation of the set S with the surface $F(X,t)$, i.e., in minimizing the functional $J[F]$ representing summary Euclidian distance between the set S and surface F:

$$J[F] = \sum_{k=1}^{m} distance(F(X, t), S_k) \tag{2.a}$$

$$S_k \in V_{feasible}(F(X, t)), \tag{2.b}$$

$$X_l \leq X \leq X_u, \tag{2.c}$$

where $V_{feasible}(F(X, t))$ is a convex or non-convex set formed as a union of orthants dominated by points belonging to surface $F(X,\ t)$. Usually, $V_{feasible}(F(X, t))$ is referred to as a feasibility set (or feasible region of a tradespace). The real-world meaning of constraint 2.b is that no technology can surpass the current technological frontier. Equation 2.c constraints vector X with physical limits.

Note that the union of two convex sets is not necessarily convex. The region lying below the Pareto frontier in Fig. 2b is feasible and non-convex. Feasibility sets that do not hold the convexity assumption are quite common in engineering practice.

Equation (1) is an implicit form of a multi-dimensional technology frontier. From now and on, we will use an explicit form of a surface solved for time t:

$$t = T(X) \quad (3)$$

The scalar field t defined on X shows at which point of time the technology reach performance level X.

The shape of the surface $T(X)$ is not arbitrary. Empirically, we know that technologies evolve following certain paths that may be approximated by linear, exponential, or S-shaped functions referred to as growth-curves (Wissema, 1982). Consequently, we can add a functional form assumptions (equality constraints) on $T(X)$ in a way that the change of a field T along chosen dimension x_k has a growth-curve shape:

$$T(x_1 = \chi_1,\ x_2 = \chi_2, \dots x_k,\ \dots, x_n = \chi_n) = g(x_k).$$

Secondly, isochrones of $T(X)$, $T(X) = \tau$ represent the state-of-the-art of technology (Pareto frontier) for a given year τ. As previously mentioned, the form of technology frontier may violate convexity assumptions. However, it is quite rare that a frontier is non-monotonic or discontinuous. Therefore, we should also add a number of non-functional form assumptions (inequality constraints) on partial derivatives of $T(X) = \tau$.

To solve this problem with a linear programming solver, we need to reformulate the continuous problem into a discrete problem. We will be looking for values of t in nodes of the Cartesian grid G_X defined in n-dimensional space $\mathbb{R}^n$ of technology FoMs $t = T(G_X)$, with two types of assumptions on the shape of T:

- non-functional assumptions:
  - along all directions of space X, scalar field t is either decreasing or increasing sequence (depending on the orientation of elements of vector X);
  - in cross-sections of t, isochrones (Pareto frontiers) are either convex or concave (t should not experience strong discontinuities);
- functional assumptions:
  - For one or number of elements of X we can write: $t = g(x_i)$, where $g(\cdot)$ is a growth curve (Gompertz, logarithmic, linear, etc.).

One can formulate a corresponding concrete optimization problem by following the algorithm:

1 Create Cartesian grid $G = (i_1 \cdot dx_1, i_2 \cdot dx_2, \dots, i_n \cdot dx_n) \mid i_1,\ i_2, \dots,\ i_n \in N$ in R^n, so we can write a discrete function $X = (x_1, x_2, \dots, x_n) = X_d(i_1,\ i_2, \dots, i_n)$ that returns coordinates of grid nodes based on indexes of grid G.
2 Define orientation and bounds of each component of vector X.
3 With respect to each node of grid G, find minimal year among observations lying in the dominating orthant $V(X_d(i_1,\ i_2, \dots, i_n))$ based on available data $C \subset S$: $T_{min}(X_d(i_1,\ i_2, \dots, i_n)) = min_t(C) \mid C \in V(X_d(i_1,\ i_2,\ \dots,\ i_n))$. In other words, among all observations with superior performances than a target (values of the grid node) we find the earliest date. Discrete functions $T_{min}(X)$ and $T(X)$ form corresponding matrices T_{min} and $\mathbf{T}$ with elements $t_{min\, i_1,\ i_2, \dots, i_n}$ and $t_{i_1,\ i_2, \dots, i_n}$.
4 First non-functional assumption:

if x_j is output-oriented, then: $t_{i_1,\ i_2, \dots, i_j = u, \dots, i_n} - t_{i_1,\ i_2, \dots, i_j = u-1, \dots, i_n} \geq 0$,

for $\forall\ u$, j; if x_j is input-oriented, then $t_{i_1,\ i_2, \dots, i_j = u, \dots, i_n} - t_{i_1,\ i_2, \dots, i_j = u-1, \dots, i_n} \leq 0$,

a *for* $\forall\ u, j$;
1 Second non-functional assumption:

if in a cross-section x_j, x_k, isochrones are convex then:

$$t_{i_1,\ i_2, \dots, i_j = u-1, \dots, i_k = v, \dots, i_n} - t_{i_1,\ i_2, \dots, i_j = u, \dots, i_k = v, \dots, i_n} - -t_{i_1,\ i_2, \dots, i_j = u+1, \dots, i_k = v, \dots, i_n} + t_{i_1,\ i_2, \dots, i_j = u+2, \dots, i_k = v, \dots, i_n} + + t_{i_1,\ i_2, \dots, i_j = u, \dots, i_k = v-1, \dots, i_n} - t_{i_1,\ i_2, \dots, i_j = u, \dots, i_k = v, \dots, i_n} - t_{i_1,\ i_2, \dots, i_j = u, \dots, i_k = v+1, \dots, i_n} + t_{i_1,\ i_2, \dots, i_j = u, \dots, i_k = v+2, \dots, i_n} \geq 0 \mid \forall\ u, v$$

$T_{min} - T$.

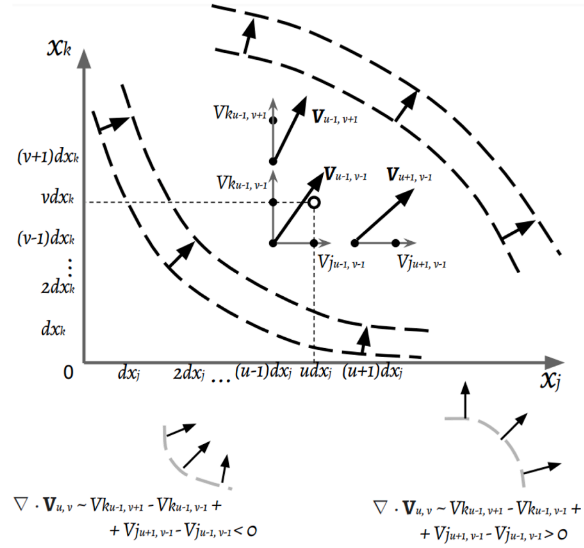


Fig. 3. Explanation to the convexity assumptions

if in a cross-section x_j, x_k isochrones are concave, then:

$$t_{i_1, i_2, \cdots, i_j = u-1, \cdots, i_k = v, \cdots, i_n} - t_{i_1, i_2, \cdots, i_j = u, \cdots, i_k = v, \cdots, i_n} - t_{i_1, i_2, \cdots, i_j = u+1, \cdots, i_k = v, \cdots, i_n} + t_{i_1, i_2, \cdots, i_j = u+2, \cdots, i_k = v, \cdots, i_n} + t_{i_1, i_2, \cdots, i_j = u, \cdots, i_k = v-1, \cdots i_n} - t_{i_1, i_2, \cdots, i_j = u, \cdots, i_k = v, \cdots, i_n} - -t_{i_1, i_2, \cdots, i_j = u, \cdots, i_k = v+1, \cdots, i_n} + t_{i_1, i_2, \cdots, i_j = u, \cdots, i_k = v+2, \cdots, i_n} \leq 0 \mid \forall u, v$$

See Fig. 3 for the clarification of the latter. These formulas are obtained by finding gradients of the scalar field and calculating the divergence using the basic definition:

$$\nabla \cdot (V(x, y)) = \frac{\partial V_x(x, y)}{\partial x} + \frac{\partial V_y(x, y)}{\partial y}.$$

1 Functional-form assumption:

Linear along x_j: $t_{i_1, \dots, i_j = u, \dots, i_n} - t_{i_1, \dots, i_j = u-1, \dots, i_n} = t_{i_1, \dots, i_j = u+1, \dots, i_n} - t_{i_1, \dots, i_j = u, \dots, i_n} \mid \forall\ u$

Gompertz along x_j:

First, x_j should be transformed by the linear form of Gompertz curve formula $y_j = log\left(-log\left(\frac{x_j}{L}\right)\right)$, where L is the physical limit of x_j. Then the equality constraint for optimization problem will have the same linear form $T(Y_d(i_1, \dots, i_j = u, \dots, i_n)) - T(Y_d(i_1, \dots, i_j = u-1, \dots, i_n)) = T(Y_d(i_1, \dots, i_j = u+1, \dots, i_n)) - T(Y_d(i_1, \dots, i_j = u, \dots, i_n)) \mid \forall\ u$

Finally, y_j should be transformed back $x_j = L\ exp(-exp(y_j))$.

Piecewise-linear approximation of S-curve: $a(t_{i_1, \dots, i_j = u, \dots, i_n} - t_{i_1, \dots, i_j = u-1, \dots, i_n}) = t_{i_1, \dots, i_j = u+1, \dots, i_n} - t_{i_1, \dots, i_j = u, \dots, i_n} \mid \forall\ u$, where $a > 1$ on an accelerating growth part of the S-curve and $a < 1$ on a slowing growth part.

1 $F(X)$ shall dominate S (no technology surpass the frontier):

$$\mathbf{T_{min}} - \mathbf{T} \geq 0.$$

2 Finally, to solve the problem, we need to minimize the distance between the technology frontier and the best technology performances at the time. Hence, now we can formulate the objective function of the linear optimization problem in the following form:

$$\mathbf{T_{min}} - \mathbf{T}.$$

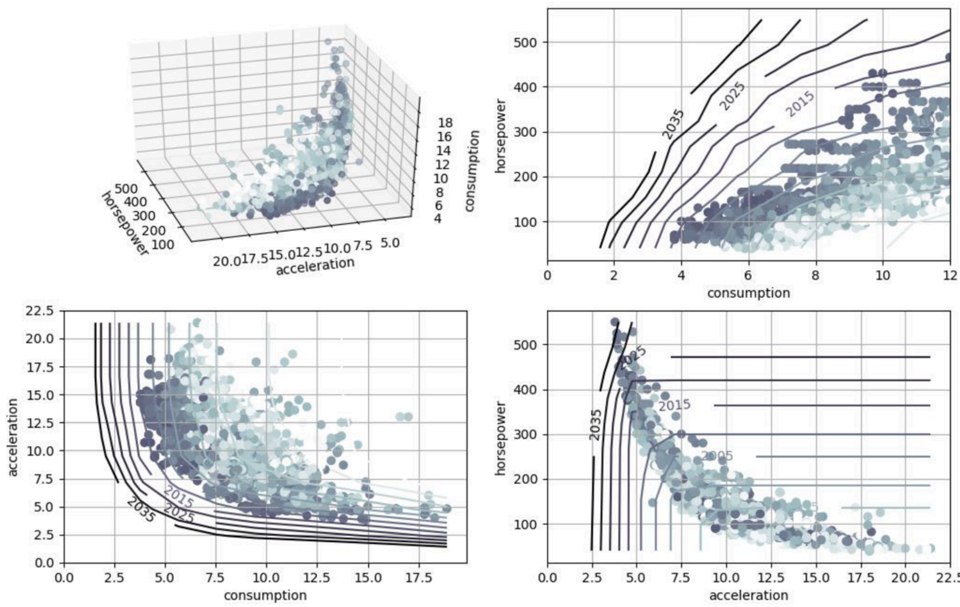


Fig. 4. Results of forecasting procedure (darker colors signify later dates)).

3.2. Game-theoretic planning

In competitive markets, companies try to release their products earlier or close to each other in order to increase their market share. Before the new model is released, the company announces its ambition and their competitors take this information for consideration.

The formulation of N-player games is an extension to Smirnova et al. (2018). There is a highly competitive technological market with N companies denoted by $C_1, C_2, \dots C_N$ where a company C_i obtains an information set (n_i) (over $i \in N$) The information sets of the companies are such that C_j (over $j \in N$) has access to the action of C_i. Each company knows the state of the game at every level of play.

Technology competition takes place in the form of a sequential game. All firms are exploring a technology tradespace to see and invest into feasible architectures. These architectures are Pareto optimal and are located on time-variant Pareto frontiers at the technology tradespace. They are considered as strategies to decide upon. Stated above leads to an extensive form of an N-person finite game with a tree structure (with a specific vertex indication the starting point of the game).

There is a finite number of available strategies for each firm to choose from. Therefore, company C_i has a set of alternatives $S^i_{n_i}$ with elements s_i at the nodes belonging to the information set n_i. If company C_j chooses a strategy $s_j(n_i) \in S^j_{n_j}$, and this so for all $j \in N$, then the outcome (so-called utility) obtained by C_j is a number $a^j_{s_1, s_2, \dots s_N}$. The set of alternatives for each player is the same at all information sets.

A (real-valued) utility function defines the possible objective $a^i_{s_1, s_2, \dots s_N}$ of company C_i and is denoted by $U_i = f(s_1, s_2, \dots s_N)$. It is a transitive, complete, continuous and convex function. This utility function ranks different strategic options and represents the company's preference over other available strategies. The outcome number is given in target FoMs and is assigned to each terminal vertex of the tree.

Thus, a unique outcome of a single game (shown holding in a separate timeframe) is an ordered N-tuple of all these numbers (over $i \in N$), i.e. $(a^1_{s_1, s_2, \dots s_N}, a^2_{s_1, s_2, \dots s_N}, \dots, a^N_{s_1, s_2, \dots s_N})$. All decisions are made independently and each enterprise seeks a maximum possible outcome, considering possible rational choices of other companies.

An N-company technology competition takes a form of a non-zero-sum finite game in extensive form. An N-tuple of strategies $(s^*_1, s^*_2, \dots, s^*_N)$ with $s^*_i \in S_i$, $i \in N$, is said to constitute its $i \in N$ Nash equilibrium (Nash, 1950) solution if the following N-inequalities are satisfied for all $s_i \in S_i$, $i \in N$:

$$
\begin{aligned}
U^*_1 &\equiv U_1\left(s^*_1, s^*_2, \dots, s^*_N\right) \geq U_1\left(s_1, s^*_2, \dots, s^*_N\right) \\
U^*_2 &\equiv U_2\left(s^*_1, s^*_2, \dots, s^*_N\right) \geq U_2\left(s^*_1, s_2, \dots, s^*_N\right) \\
&\dots \\
U^*_N &\equiv U_N\left(s^*_1, s^*_2, \dots, s^*_{(N-1)}, s?^*_N\right) \geq U_N\left(s^*_1, s^*_2, \dots, s^*_{(N-1)}, s_N\right)
\end{aligned}
\tag{4}
$$

The N-tuple of quantities $(U^*_1, U^*_2, \dots, U^*_N)$ is a Nash equilibrium outcome of the non-zero-sum game in extensive form. The strategies $(s^*_1, s^*_2, \dots, s^*_N)$ correspond to the best response strategies to the opponents' strategic choices and $s^*_i \in BR_i(s^*_1, s^*_2, \dots, s^*_N)$.

Limitations. The extensive form implies a certain players' sequence of deciding upon strategies: who reacts first, who is second, etc., and the determination of further best response sets. A number of order variations is found as $k = N!$ and each variant leads to different architecture outcomes and corresponding FoM values. It is computationally impossible to calculate all architecture outcomes and paths for a big number of companies.

According to Vincent (1983), the determination of the best response sets can be quite difficult. If they are not determined numerically, then a number of scalar optimization problems would have to be solved in order to define the sets. The best response functions can be represented as linear or nonlinear functions with one or more Nash Equilibria with an axis of the variables (Hey et al, 2007). The geometrical character is unknown and therefore the problem of determining reactions is reduced to the use of a multivariate linear regression approach based on the made assumption of best response function linearities in Smirnova et al. (2018). In addition, while forecasting reactions for each player in separately standing m, its number to be determined, $m = M^k$ grows in geometrical progression with every game level: $m = M^k$ where M is a number of FoMs under consideration and k is a level of a game.

4. Illustration of the methodology on a case study

4.1. Pareto-frontier forecasting

In this section, a case study on the automotive industry is described, to demonstrate our proposed methodology. Despite the rapid growth of hybrid and electric vehicles, cars with gasoline engines will be still dominating in the following 10-15 years. The abundance of historical data enables robust trend-forecasting study. The pursuit of fuel

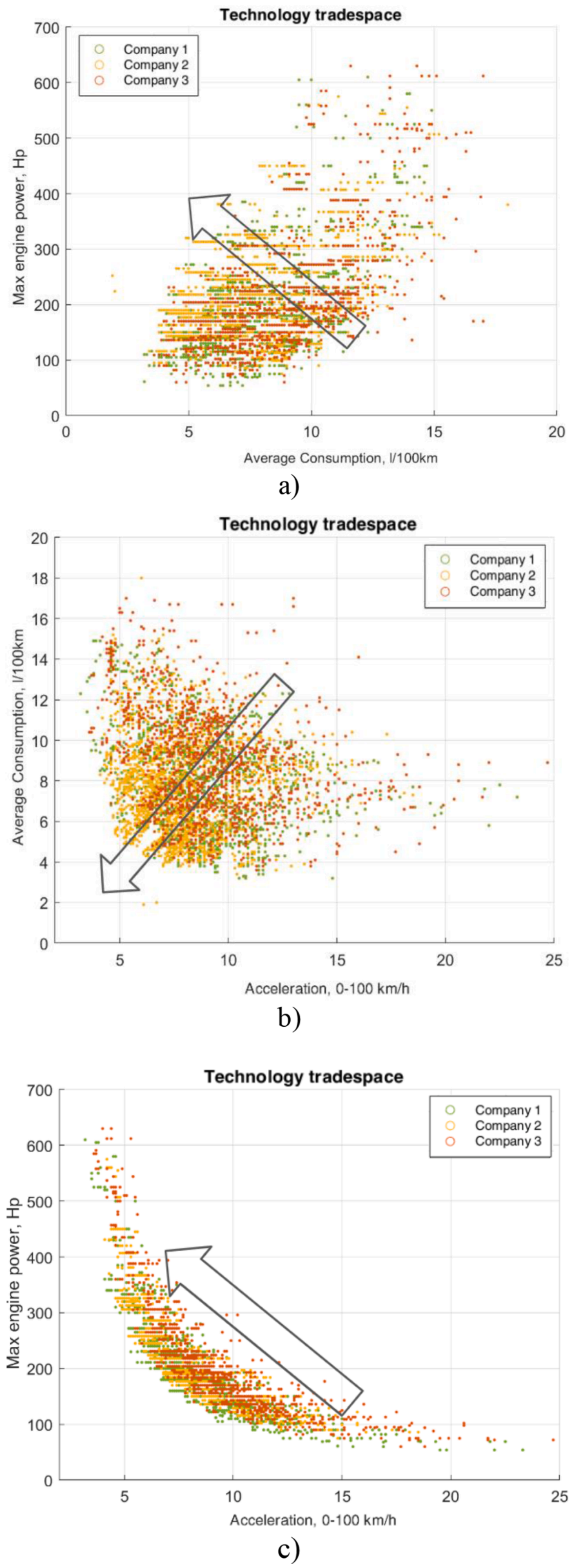


Fig. 5. Technology tradespace of players with FoM trends.

efficiency has become the major driver of innovations in this field due to government regulations and users' economic considerations. For driving experience, car manufacturers strive to maximize engine power and vehicle acceleration. These two FoMs are highly correlated, but strictly speaking, not fully equivalent. Ideally, users would like to maximize both. Acceleration affects mainly the driving experience, while higher power of the engine with the same level of acceleration also improves loading capacity and off-road performances.

The database used in this case study (obtained from open web-resource (Car specs database, 2020) consists of 3,289 data points and encompasses car models from 32 car brands from all major automotive companies. The results of applying the proposed algorithm to this dataset are shown in Fig 4.

We propose the following heuristic formula for the estimation of the statistical significance of the dataset used for the multi-dimensional frontier forecasting:

$$M \sim \left(\frac{\sigma_{sample}}{\sigma_{target}}\right)^2 \cdot \prod_{i=1}^{n} p_i,$$

where M – sample size, σ_{sample} – estimated standard deviation of observations, σ_{target} – expected accuracy of frontiers approximation, n – number of dimensions, p – parameter that determines the minimum number of points required for the determination of the frontier's shape along each of the dimensions. For example, if the number of dimensions is 4 (3 FoMs and time), p along all dimensions equals to 3, target accuracy is 1.0 year, and standard deviation of the sample is 5.0 years, then and the minimal statistically significant amount of points is about 2025. The proposed formula gives rough estimates due to the uneven distribution of points in a tradespace (real accuracy will be lower in some regions of a tradespace), so it needs to be adapted for concrete datasets.

4.2. *Game-theoretic planning*

The database considered in this study includes data from over 30 carmakers. To show the visibility of framework with a number of players more than 2, three companies, (C_1, C_2, C_3) are chosen as major competitors with comparable models belonging to different tradespace areas. First, it is important to understand who is a "technology pioneer" and who is a "follower" out of the taken companies by studying their car designs at a 3-FoM tradespace (Maximum engine power – Average consumption – Acceleration). Fig. 5 a, b and c displays released automobiles between 1979 and 2013 with FoM trends exposing their evolution directions. It is inferenced that the models have almost identical characteristics and are compatible based on minimum distances between plotted data points in 3 different projections of a chosen tradespace. Overall, Company C_2 is the closest to the edge of the tradespaces Horsepower-Consumption and Consumption-Acceleration, which leads to the assumption of its pioneering role. The other two players seem to be "followers", the companies producing models close to the pioneer's ones after its respective model releases.

An important variable is a sequence of company's reactions to competitor's responses. In this case, there are 6 possible variations for

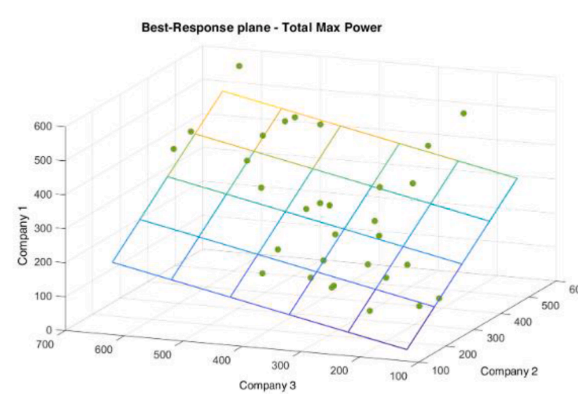


Fig. 6. Best-Response plane of Total Max Power for Company 1.

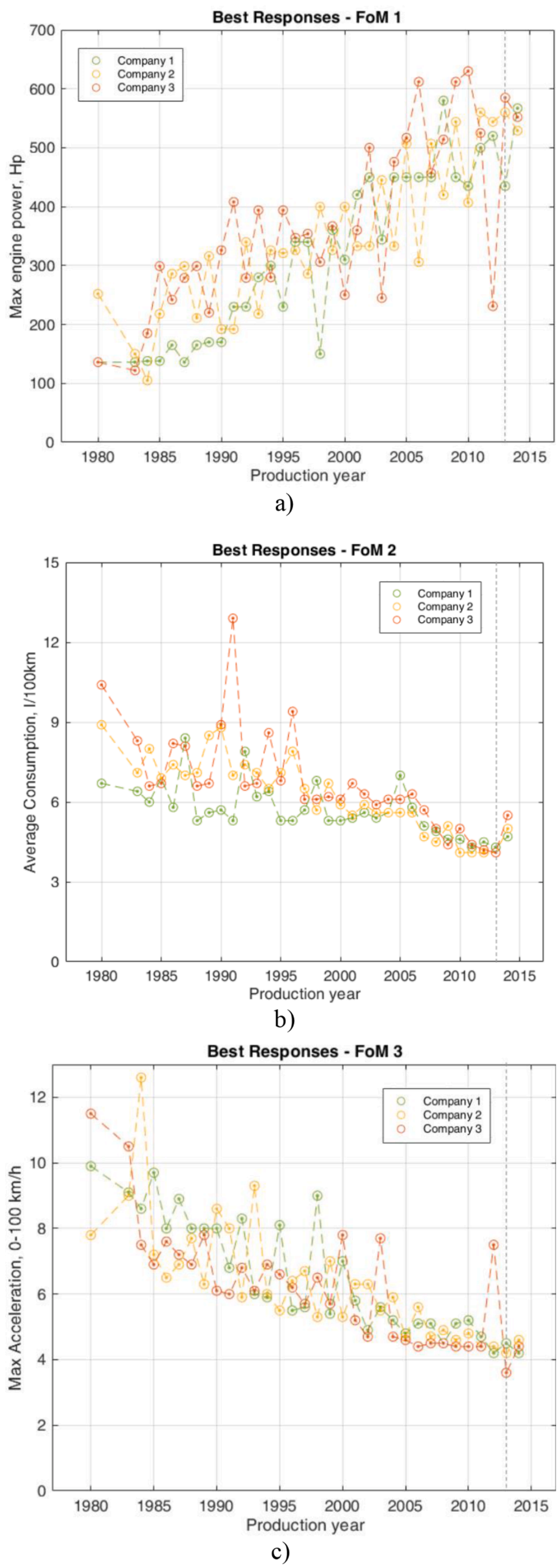


Fig. 7. Best Responses over time.

the 3 players: $C_1C_2C_3$, $C_1C_3C_2$, $C_2C_1C_3$, $C_2C_3C_1$, $C_3C_1C_2$, $C_3C_2C_1$. There is no strong preference above any of the stated sequences. The chosen sequence in the following is $C_1C_2C_3$: Company 1 reacts first, then Company 2 and Company 3 the last.

Historical data about manufactured and released models (Fig. 5 a,b and c) is considered to be previous technology development by companies and is used to approximate the BR functions. The intersection of those BR functions is the Nash Equilibrium which presents a goal for competitors. The last known or chosen companies' positions are marked on approximated BR functions in order to get a reaction to other competitors' "move" or released model in our case.

Whereas in a 2-player case, a best-response function is a function line in a 2-D representation showing all possible reactions to competitor's model choice; in a 3-player case it forms a plane. Fig. 6 shows such a plane for past reactions on Power FoM, obtained by multivariate linear regression with R-squared 0.79 using a similar approach as in Smirnova et al. (2018) The level of dependence is slightly lower compared to a 2-player case. However, it shows a moderate linear relation between competitors' levels. It can be seen that Company 1 has reacted by lower levels and couldn't steadily jump over other companies. The same planes are built for the other competitors in order to get next reactions to the latest models.

The intensity of competition is seen in the closeness of Best Responses (BR) in separate FoMs (Fig. 7.a-c). Best Responses are found without specifying Nash Equilibrium solutions for each known year. The BR in one FoM does not always mean a Best Response in the other. The difference of FoM levels is decreasing over time which seems to make the models to be interchangeable based on a selected set of characteristics. It can be concluded the FoM levels of BR models are converging and reaching their physical limits.

Full information (without unknown values or Not-a-Number (NaNs)) about car models is available till 2013 (vertical line at Fig. 7.a-c). Next best responses (2014) beyond the dataset are demonstrated for all companies and FoMs after the last known year at Fig. 7.a-c. FoM reactions and possible architectures for next years can be shown with the use of forecasted Pareto frontiers. They are intersections of best responses with frontier lines. Based on this, there are three major directions for formulating best responses:

- improve the engine power figure of merit (formed by the power BR reaction);
- improve the average consumption (formed by the consumption BR reaction), and
- improve the acceleration which is resulted in in-between directions in the tradespace (formed by the acceleration BR reaction).

The intersection of all three best responses forms a utopia point. The utopia point represents an ideal architecture which is located beyond the Pareto frontier of the current technology level. It is omitted during discussion and selection because of the limited technology level in the current time period.

Based on the number of reasons, 3-5 years is a period limit for the framework. There are several reasons behind the choice:

1 Long-term planning can be interrupted by disruptive innovations and technologies;
2 Computational consumption increases with a number of years growing. In total, 3,375 reaction and intersections with frontiers should be determined for 5 years with 15 levels (3 levels per year) of games;
3 Significant errors might occur because of a company's internal unknown factors which define the overall direction of their car models' development.

5. Validation

In this section, a validation approach and associated results are shown with a discussion on the obtained errors. Backward testing is selected as a general approach for validation involving splitting the original data for a given year and calculating differences and errors

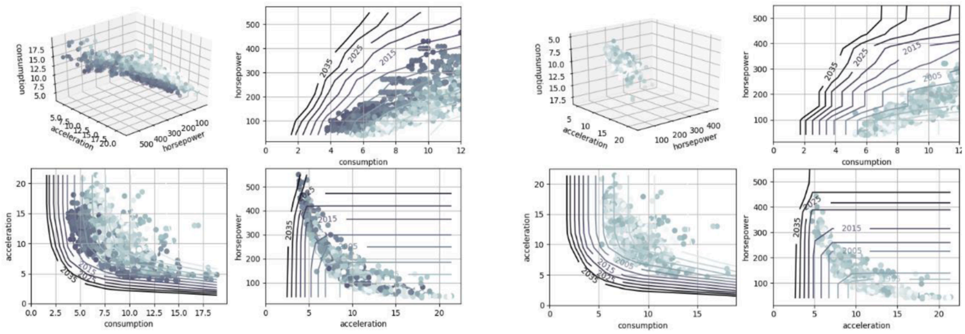


Fig. 8. The results of the frontier forecasting for full (1971-2016) and cut (1971-1996) dataset.

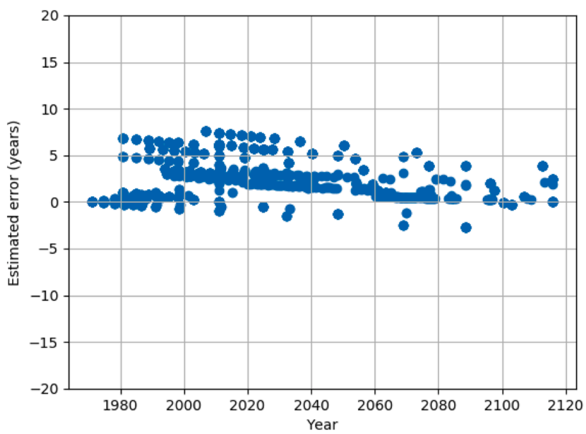


Fig. 9. Frontier forecasting error (in years).

between actual data and predictions.

5.1. *Multi-dimensional Pareto frontier forecasting*

Generally speaking, to prove our ultimate hypothesis that multi-dimensional Pareto frontier forecasting improves the utility and accuracy of quantitative (numeric) roadmaps in the context of a big company, one needs to conduct the observational study in technology management department of a real company. The main questions for this study would be the following:

- is there enough historical data about key technologies to make accurate predictions;
- are the produced predictions worth the effort of gathering data;
- how often the company resorts to quantitative technology forecasts and how often to qualitative.

Such a study is out of the scope of this paper. Instead, we present here an internal validation of the algorithm to test the sensitivity of the results to the variations in input data.

We utilize the idea of backward testing. We cut the full dataset with some past threshold year to see the current state-of-the-art prediction accuracy. By doing this, we calculate the accuracy of the forecast as if it was done in the past.

Fig. 8 shows the Pareto frontiers calculated for the full and cut dataset, respectively. The forecasting error is calculated as an absolute difference between results obtained for the full t_{full} and cut t_{cut} dataset in each node of the Cartesian grid G. In Fig. 9 the error scatter plot is shown. The mean value of forecasting errors equals 2.8 years, which means that if our assumptions regarding growth-curve and frontier shapes are correct and the general trend will not experience the dramatic change, a performance forecast for the next 20-years has an accuracy of around 15%.

The calculated accuracy of the backward test, however, depends on input parameters: variation of the grid size, piecewise-linear approximation coefficient a, threshold year t_{cut}, etc. Therefore, the authors recommend performing parameters tuning for every new dataset.

The expression for forecasting error for the backward test is the following (for each node of the grid G):

$$\Delta t = t_{full} - t_{cut}.$$

5.2. *Game-theoretic planning*

The key objective of validation is to get possible "moves" or directions for development via models on Pareto frontiers and compare them to the real Best Responses of the following year. The number of years which contains full data about companies C_1, C_2, C_3 (released models are known for each company) is only 30 epochs (1979-2013). For validation the last available (threshold) year is cut to compare released Best Responses models with suggested ones (predicted Best Responses models) by the algorithm based on the approach presented in the paper in the context of 3 FoMs and possible evolution paths. The threshold year is 2013: a Pareto frontier is built for this year; the Best Response models are predicted based on BR planes; the actual models released by the companies are known and analyzed. The FoMs (Total Max Power, Average Consumption, Acceleration) are chosen as critical and significant for the following technology. While every model is a tradeoff of the FoMs which are interconnected, a player (or the company in the following case) could prefer one upon the others. This preference prioritizes a model among others with similar characteristics, but with worse in the prefered FoM, or a priority merit. A priority merit means that a preference of BR is given to a forecasted model with a better FoM value. For example, if a priority merit is Total Max Power, then a BR is a model with this highest FoM out of other enumerated variants. Due to 3 priority FoMs, 3 evolution pathways are studied: each devoted to one priority merit. (Fig. 10.d-f).

Fig. 10 a, b, c, d, e and f present the calculated (predicted) models found as the intersection of regressed BR with a Pareto frontier and the released models (real manufactured models) by companies in 2013. First, Fig. 10. a, c and e (on the left) show all possible models (blue circles) for 2013 suggested by the presented approach in terms of all 3 FoMs which are selected as a priority merit one by one for companies. According to the chosen sequence of company's reactions, Company 1 reacts to the latest model of Company 3 that gives 9 possible outcomes. Further, Company 2 reacts to each defined model. Second, the plots on the left show all manufactured and released models (green, orange, and red circles) by companies in 2013.

All suggested models found as the intersection of Best Response in the following FoM and the 2013 Pareto frontier are analyzed for which are the Best Response model for the priority merit. It leads to one BR model selected per each priority FoM (Table 1). In Table 1 each BR model is presented in the following format - (Total Max Power; Average

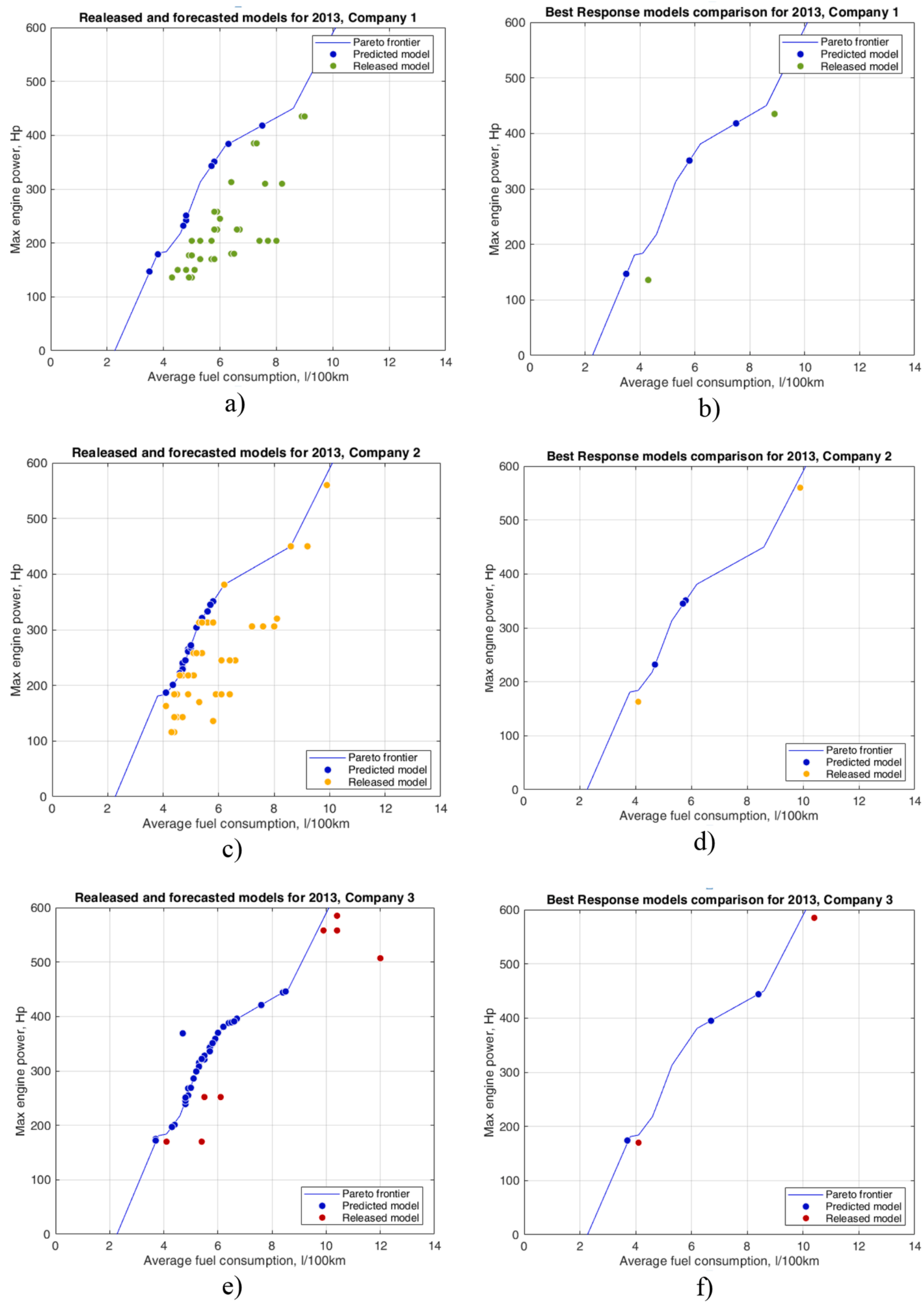


Fig. 10. Visual comparison of predicted (suggested) models with released models of players.

Table 1
Calculated BR models in terms of the priority FoMs.

	Total Max Power, Hp	Average Consumption, l/100km	Acceleration, km/h
Company 1	(418; 7.5; 4.6)	(147; 3.5; 8.9)	(351; 5.8; 4,9)
Company 2	(351; 5.8; 5.0)	(232; 4.7; 6.2)	(345; 5.7; 5)
Company 3	(444; 8.4; 4.6)	(174; 3.7; 7.86)	(395; 6.7; 4.7)

Table 2
Released BR models in terms of the priority FoMs.

	Total Max Power, Hp	Average Consumption, l/100km	Acceleration, km/h
Company 1	(435; 8.9; 4.5)	(136; 4.3; 9.3)	(435; 8.9; 4.5)
Company 2	(560; 9.9; 4.2)	(163; 4.1; 8)	(560; 9.9; 4.2)
Company 3	(585; 10.4; 3.6)	(170; 4.1; 8.4)	(585; 10.4; 3.6)

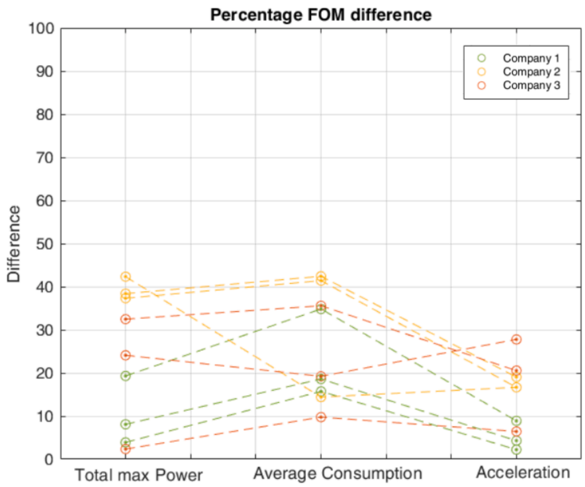


Fig. 11. Percentage FOM difference in Best Response models.

Consumption; Acceleration).

All the real released models are analyzed in the same way as calculated models in order to state the BR model for the year under consideration and comparison (Table 2). The same BR models are chosen for 2 FoMs, Total Max Power and Acceleration.

Fig. 10. b, d and f (on the right) show those selected Best Response models out of the whole scope of predicted and released ones shown in Fig. 10. a, c and e (on the left). The released BR models don't form the Pareto frontier and stand slightly behind from it in spite of this they exceed the calculated BR models in certain FoM characteristics.

Overall, C_1 gets better results due to the 1st mover; the 3rd mover C_3 gets the worst results. FoM differences are presented in Fig. 11 in percentage. Those percentage differences are calculated between FoM characteristics of selected BR models in Table 1 and 2 accordingly in terms of each FoM level. The percentage difference shows a prediction error of BR functions based on the accuracy of done regression and found intersection with a Pareto frontier. For C_1: the biggest difference is in Max Power interpretable by a "follower" position at tradespace. C_2 results are in average at the same level for all FoMs.

Based on Fig. 11 visually it can be concluded that a priority merit, Acceleration, got the most accurate results. The average difference for FoM 1 and FoM 2 for all companies' models is 25% with a FoM value of released models; FoM 3 exhibits a difference of 15%. Comparing only priority FoMs values in the suggested models shows a difference in Total Max Power if 21%; -13% Average Consumption, and -20% Acceleration. These levels of differences can be explained by the reasons of:

- Non-linear character of Best-Response dependences between companies;
- "Pioneer" or "Follower" roles of players within a tradespace;
- Approaches of Pareto-frontiers calculation;
- Unavailable internal information (strategy, prototypes, etc.) which affect released model architectures.

The obtained results don't show large differences so that gives an empirical validation of the proposed approach[1]. Nonetheless, the set assumptions in the framework idealize the technology competition which is rarely met in real market situations and influence the results. The extreme assumptions are taken in the game under discussion what should be challenged.

6. Conclusions

Availability of large amounts of data on the complex systems design past experience opens the road for the application of data science methods and tools to the domain of systems engineering and technology management. Being fully numeric, these approaches help to reach a higher level of formalization and automatization, overcome biases and facilitate decision making even in the fields where human creativity plays a key role.

Multi-dimensional Pareto frontier forecasting is a method based on the idea of technology forecasting by extrapolation of past trends in the future. We proposed an algorithm that overcomes limitations of existing algorithms and tested it on the case of the forecasting of fuel efficiency of cars with petrol engines. The obtained average forecasting error is less than 3 years for a forecast period of more than 20 years, making the proposed approach usable for quantitative technology forecasts (at least for datasets with similar properties). The proposed methodology's difficulty is that datasets of the past technology evolution need to be relatively large (thousands of points even for the 3-dimensional case). The results of multi-dimensional forecasting can be used for technology planning and roadmapping. Specifically, we suggest using multi-dimensional Pareto frontiers combined with multi-dimensional demand curves to support the planning of disruptive innovation strategies.

Another limitation of the proposed approach is the possibility of a forecast distortion caused by external factors. For example, environmental concerns lead to changes in policies. In their turn, policies change the investment dynamics into internal combustion engine technologies, invalidating forecasts based on the trend extrapolation concept.

The goal of game-theoretic technology planning is to give an understanding of possible direction for model involvement based on competition and dependence. It is a method based on the idea of interdependent technology evolution of key tradespace players. The average obtained precision is around 20% with a set of extreme assumptions of the considered game. This approach is a new view on application of game theory in technology planning and roadmapping. In combination with Pareto-frontier forecasting, it advances the process of technology planning by providing technology insights essential to strategy decision-making. The goal of further research is to find theoretical fundamentals, to prove the obtained results and to challenge the assumptions taken in the present work (complete information set, linear best response functions) for better approximation of practical problems in real environments. A second area of interest for future research is to address the fuzzy (stochastic) nature of technology frontiers. We foresee conducting a comparative study to calculate the accuracy of different approaches of multi-dimensional technology forecasting and clarify their limitations.

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