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Strategic planning of new product introductions: Integrated planning of products and modules in the automotive industry☆

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ABSTRACT

Timing the introduction of new products to the market is an important strategic decision in the automotive industry. For several reasons, it is also a complex decision problem. First, the use of platforms creates many interactions between different vehicles via shared modules (e.g. engines). Second, new and existing products rely on various shared resources (e.g. development resources or production capacities). Furthermore, different conflicting objectives must be considered. In this paper, we develop a mathematical linear programming model describing the decision problem based on the resource-constrained project scheduling problem. It simultaneously decides on the start of production date for vehicle models, variants, and engines as well as on the assignment of engines to the given variants. Integrating a multi-criteria approach, the model helps to analyze trade-offs between important managerial objectives related to resource utilization and fleet emission metrics. Using realistic data from a major European automotive company, we demonstrate that our model enables the efficient evaluation of various courses of action. Such capabilities are especially relevant in times of rapid technological change, such as the current transition towards electrified vehicle portfolios.

1. Introduction

Since almost three decades, mass customization [1] is common practice in many industries to efficiently serve customers with personalized products. The underlying challenge is to offer a wide range of products while developing and producing them efficiently. A well-established approach to address this challenge, particularly in the automotive industry, is the use of modular, platform-based products [2]. Modules are defined as subsystems of products with standardized interfaces such that they can be shared among various products [3]. Extending this idea, platforms can be described as a set of subsystems and interfaces that allow to efficiently develop and produce a stream of derivative product variants [4].

As an illustration of modular product structures and corresponding life cycle decisions, we can for example look at the automotive industry. Here, manufacturers frequently offer various vehicle models (referred to as models in the remainder of this paper), such as sedans and station wagons. These models can share various characteristics, e.g. the wheelbase, but differ with respect to other characteristics, e.g. the body style. When different models share characteristics as the wheelbase, they are considered part of a product family. Table 1 shows examples of this structure for some of the large European automotive manufacturers. Here, a product family could be all E-class models by Mercedes or all 5 series models by BMW. A distinct model is then for instance the Audi A6 Sedan.

In addition to the model distinction, customers can usually choose from a variety of different engines, such as combustion engines, electrical engines, as well as hybrid engine combinations. In order to reduce the development and testing effort, engines are usually shared among various models. Models are used in a modular product structure. This means that for instance Mercedes' E-Class Sedan and their C-Class Estate could be sold with the same engine. These combinations of models and engines are called variants (e.g. an Audi A6 Sedan diesel), and they are the basic structure of product portfolios in this industry.

Managing such a modular product portfolio does however lead to many product life cycle decisions, mainly related to (1) the timing of models, variants, and engines, and (2) the assignment of engines to models. Although platforms generally consist of multiple modules, we focus in this paper on engines as the most relevant

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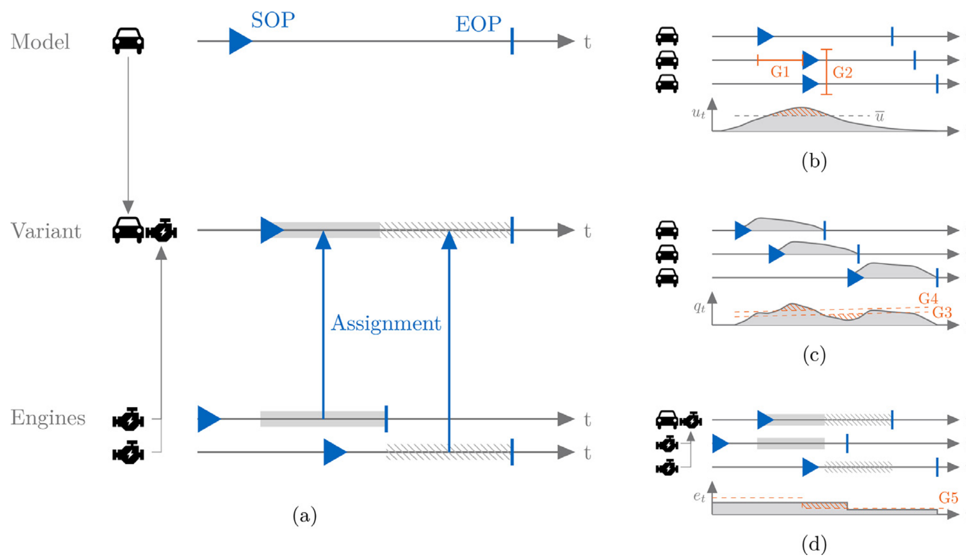


Fig. 1. Planning problem (decisions in blue, goals in orange for a colored figure, the reader is referred to the web version of this article).

Table 1
Illustrative example of product families and corresponding models.

Product Family	Model	Audi	BMW	Mercedes
Large	Sedan	A6 Sedan	5 Series Sedan	E-Class Sedan
	Wagon	A6 Avant	5 Series Touring	E-Class Estate
Medium	Sedan	A4 Sedan	3 Series Sedan	C-Class Sedan
	Wagon	A4 Avant	3 Series Touring	C-Class Estate

module (while our approach could be extended to include multiple modules). The resulting decision problem is illustrated in Fig. 1a. Based on the technology roadmap, planned models and engines have to be combined into variants. Generally, each model is offered in multiple variants, i.e. a customer can order a model with one of various engines. As the product life cycles of the models and engines is not always perfectly aligned, variants might also change to newer engine generations at some point in the model's life cycle.

The relevant timing decisions are the start of production (SOP) and end of production (EOP) for each model, each variant, and each engine. These decisions need to respect time windows resulting from the general platform structures outlined in the technology roadmap, e.g. the earliest availability due to technological evolution. In Fig. 1a, the SOPs and EOPs are depicted by triangles and bars, respectively. The time span between SOP and EOP is typically several years and within this time span thousands of units are manufactured. Between the SOP and EOP of models and variants, it has to be decided which engines to assign in which period (the arcs in Fig. 1a). Here, the compatibility of engines and variants as well as the engine availability needs to be respected. Besides, each engine assignment leads to additional development and testing effort. Therefore, manufacturers are often not able to assign the latest engine generation to all model variants. As a consequence, engine generations might overlap and at any given time, a set of possible engines with their own SOPs and EOPs are available for assignment to variants.

Further complexity is introduced by the fact that timing and assignment decisions have an impact on the utilization of various shared company resources. There are different resources to consider, which often ends up pointing the timing and assignment decisions in different directions. In this paper, we consider five different performance indicators related to the planning of new product introductions, each of them having a goal that relates to the efficient use of one or more of the resources (illustrated in Fig. 1b–d).

The first goal (G1 in Fig. 1b) relates to a desired temporal distance between the SOPs of models within a product family. Certain models should ideally be scheduled within a minimum and a maximum time span in order to be developed efficiently. For instance, when introducing a sedan and a station wagon for a mid-size product family, the manufacturer usually focuses on one (lead) model first and then transfers a mature solution concept to the other model (derivative). In this case, there should be a minimum distance between lead model and derivative model to allow for the maturation, which decreases the overall demand for development resources. At the same time, there should be a maximum distance, so that the technology of the derivative is still state of the art at the market introduction.

The second goal (G2 in Fig. 1b) relates to a maximum number of simultaneous SOPs of different models. The rationale behind this restriction is that these SOPs bear considerable complexity and extra work for development and production. Hence, the number of simultaneous SOPs should be limited to avoid peaks in resource utilization [see also 5]. Together, goals G1 and G2 help the company to indirectly steer the utilization of development resources u_t and minimize exceedance of available resources $\bar{u}$. A smoother resource utilization profile is known to reduce capital expenditures on temporary equipment and avoids overloaded staff.

The third goal relates to the target sales quantity per period (G3 in Fig. 1c). Automotive manufacturers are generally large companies listed at the stock exchange, which aim to meet specific sales targets on a company level. These sales targets are, in part, communicated to shareholders and the public, and are based on knowledge from various domains such as past sales, the development of the market, the positioning of the company within the market, etc. We try to minimize any negative deviation of the planned portfolio sales q_t from the sales target (hatched area below G3) which is a first step towards a constant and reliable income of the company. The portfolio sales q_t is the sum of the sales curves from the individual variants, which usually follow typical sales patterns [6]: After SOP, production is first ramped up [7] until a maximum production rate is reached while towards the EOP, customer demand for the product decreases. As will be explained in more detail at the beginning of Section 3, these variant sales curves can be understood as a function of SOP and EOP and are the result of forecasts that are based on various factors, including historical data and other domain knowledge.

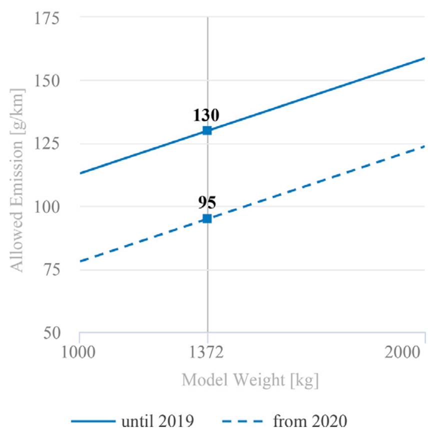


Fig. 2. The allowed emission according EU-legislation (Data source: European Parliament [8]).

The general idea of the fourth goal (G4 in Fig. 1c) is the efficient utilization of production capacities by avoiding overload. As illustrated by the hatched area above G4, any exceedance of the production capacity is to be reduced for each plant in each period.

The last goal (G5 in Fig. 1d) is considering CO_2 limits, as e.g. imposed by the European Parliament [8]. While many recent publications have studied carbon emissions of the supply chain [e.g. 9], G5 specifically focuses on the product use phase, which in many industries is responsible the majority of all life cycle emissions. In the European Union, automotive manufacturers have to ensure that the sales-weighted average of CO_2 emission e_t is below a time-dependent limit, which is currently given as an average of 130 g CO_2 per km based on an average model weight of 1,372 kg. Every additional kg of model weight allows for an additional emission of 0.0457 g CO_2, as illustrated in Fig. 2. Both average CO_2 emission and average model weight are defined as sales-weighted average per year. Thus, if a company is selling more heavier models in a specific year, the average model weight in that year goes up and the limit allows for a higher average emission. In consequence, this goal is influenced by both the average emission and the average weight of the product portfolio in any year. To provide an incentive structure for the automotive sector to move to more environmentally friendly technology, the European Union will lower the allowed CO_2 from 130 to 95 g per km in 2020.

The above-mentioned 5 goals are clearly influenced by the timing and assignment decisions made in the strategic planning of new product introductions. Despite the complex interactions between decisions and goals, automotive manufacturers address this strategic planning problem manually and iteratively in a planning process that spans across multiple departments and takes a long time to finalize. In consequence, it can neither be guaranteed that the company identifies good trade-offs between the different goals nor that planning mistakes are detected before the strategic decisions are locked in and more detailed planning starts. Especially in times of rapid technological change, manufacturers need to be able to efficiently explore various courses of action. To appropriately address these questions, a sound methodological basis is required for the strategic planning of model introductions.

In this paper, we therefore develop a multi-criteria optimization model for platform-based product introduction. The key planning problem, i.e. the timing of models, engines, and variants, as well as the engine assignment, resembles a project scheduling problem with additional resource considerations. Our modeling approach, which can be referred to as integrated life cycle and variant planning, is therefore based on the resource leveling problem (RLP). We will show that by the use of multi-mode formulations, it is possible to link timing decisions with assignment decisions. To analyze the interaction of the presented goals, our model builds on a combination of two established multi-criteria modeling approaches. The resulting insights support practitioners in assessing key trade-offs in their strategic planning process and hence enable strategic planning to provide the potentials for subsequent tactical and operational planning.

The remainder of this paper is organized as follows: In Section 2, a brief review of methods to solve the RLP is presented. In Section 3, we develop our modeling approach and describe our multi-criteria solution approach in more detail. Based on our numerical study in Section 4, we present managerial insights in Section 5. Finally, we discuss this paper and future research opportunities in Section 6.

2. Literature review

Three streams of literature are relevant for our research: 1) product portfolio planning, 2) sales and operations planning, and 3) resource leveling and scheduling.

2.1. Product portfolio planning

Companies usually aim for a product portfolio that attracts many customers while production costs are minimal. The corresponding planning problem is also referred to as product portfolio planning [10].

From a marketing perspective, this typically relates to extending the product line in such a way that additional consumer surplus is captured. Even though product line extensions potentially cannibalize the sales of existing products, the forecasted sales increase can lead to improved profitability. Wilson and Norton [11] for instance show in which cases such an introduction is interesting at all, and if it is, how this is affected by price differences and consumer purchasing behavior. The literature also provides guidance on how sales develop over the lifetime of product generations [e.g. 12,13].

From a production perspective, the question is rather how to develop and produce a variety of products efficiently [14]. For this, the use of standardized product platforms [4] is common in the automotive industry, frequently subdividing the product portfolio in several product families [1,15,16].

When linking these two perspectives, launch timings are predominantly taken as a given and the focus of previous research is on the reduction of production cost [17,18]. Only few publications address the question of product platform renewal [e.g. 19–21]. Our work aims to build on forecasted sales quantities and to determine optimal introduction times of products and modules considering multiple conflicting objectives.

2.2. Sales & operations planning

As outlined by Thomé et al. [22], sales and operations planning (S&OP) fulfills two purposes: First, it aims to balance supply and demand. Second, it helps to integrate cross-functional plans by supporting the coordination of various decision makers to better reach business targets [23]. Thereby, S&OP is studied for various planning levels reaching from the general determination of production capacities [e.g. 24] to more tactical ramp-up planning [e.g. 5,7].

Although timing decisions are at the intersection of Product Portfolio Planning and S&OP, research on the interface of both streams is lacking. In this paper, we integrate cross-functional plans via the consideration of conflicting, functional-dependent objectives as generally done in S&OP. Moreover, we develop a model that comprises both timing and assignment decisions and hence allows to study cross-functional trade-offs, especially regarding the CO_2 emission.

2.3. Resource leveling and scheduling

To model our problem, we build on the literature on the resource leveling problem (RLP). The RLP is closely related to the resource-constrained project scheduling problem (RCPSP). While the RCPSP minimizes the makespan under the assumption of scarce resources, the aim of the RLP is to use given resources efficiently within a finite time horizon [25]. According to Gather et al. [26], this is done by scheduling activities in such a way, that resources are used evenly.

Rieck and Zimmermann [27] differentiate three different types of resource leveling. First, the classical resource leveling minimizes peaks in the resource utilization expressed as a quadratic function. Second, the overload problem penalizes exceedance of a given threshold. Finally, the adjustment cost problem minimizes fluctuations of the resource usage. The goals defined in our problem are closest to the overload problem.

For both RLP and RCPSP, resource constraints as well as minimum and maximum time lags between activities [28] can be considered. With respect to resource demand, multi-mode [29] and time-varying formulations [30] have been studied before. However, to the best of our knowledge, variations in resource demand have only been studied with respect to start times and not for the combination of start and finish as needed in our case. Only few exact solution approaches have been proposed to solve the RLP [31]. As shown by Rieck et al. [32], considerable performance gains are possible by linearizing resource demand with auxiliary variables for which the domains are determined in preprocessing.

3. Modeling and solution approach

3.1. Modeling approach

We consider models, variants, and engines as activities for which we decide about start and end of production (SOP and EOP). As both start and finish have to be determined, each activity is modelled with two different nodes in an activity-on-the-node network, which are connected by an arc from the start to the finish node [33]. Start as well as finish times are at the beginning of a period. To model the assignment of an engine to a variant, we use a multi-mode concept [29], in which exactly one engine from a set of compatible engines needs to be assigned at a time. Our objective is to minimize goal deviations. The notation we use is given in Table 2.

As discussed in Section 1 and illustrated in Fig. 1, five goals are considered, which are translated into individual objective functions (1) - (5). Deviations from the target distance of derivatives are minimized by (1). With (2), we minimize the number of simultaneous model starts per product line and period that exceed a given threshold. While (3) minimizes any negative deviations from target sales, objective (4) minimizes overtime of plants. Finally, exceedance of the CO_2 cap limit is minimized in (5). Although the cost coefficients in the objectives might depend on the indices of the corresponding deltas, this information is usually not available for companies. To simplify the formulation of the objectives, we assume constant cost coefficients. In case information is available to make the cost coefficients dependent on the indices of the corresponding deltas, it could be straightforwardly considered in the model. Note that the objective functions are connected to the decision variables in different ways. While model SOPs clearly influence the first two objectives, variant and engine SOPs as well as engine assignments influence the objectives through e.g. the forecasted sales curves and the engine emission characteristics.

$$\text{Min} \quad \Delta^{dis} = \sum_{(i,j)\in I^d} \left(c^{dis-} \cdot \Delta^{dis-}_{i,j} + c^{dis+} \cdot \Delta^{dis+}_{i,j}\right) \tag{1}$$

$$\text{Min} \quad \Delta^{sim} = \sum_{l\in O^l}\sum_{t\in T} \left(c^{sim+} \cdot \Delta^{sim+}_{l,t}\right) \tag{2}$$

$$\text{Min} \quad \Delta^{sal} = \sum_{t\in T} \left(c^{sal-} \cdot \Delta^{sal-}_{t}\right) \tag{3}$$

$$\text{Min} \quad \Delta^{ove} = \sum_{t\in T}\sum_{p\in O^p} \left(c^{ove+} \cdot \Delta^{ove+}_{t,p}\right) \tag{4}$$

$$\text{Min} \quad \Delta^{co2} = \sum_{a\in T^a} \left(c^{co2+} \cdot \Delta^{co2+}_{a}\right) \tag{5}$$

The first sets of constraints describe the start and end of production (SOP and EOP). Using step variables, this formulation leads to strong LP relaxations and therefore to a favorable computational performance [34]. The start variable $x^s_{i,t}$ equals 1, if activity i starts at the beginning of period t or before. Consequently, start variables are monotonically increasing in time (6). Combined with a similar formulation of finish variables (8), this allows for checking on the status of activity i as summarized in Table 3. Also, this formulation allows to fix certain variables in preprocessing, e.g. due to time windows, and hence reduce the size of the model. All activities have exactly one start time, hence at the latest possible start $\bar{s}_i$, the start variable has to be equal to 1 (7). The same holds true for finish variables (9). Both start and finish time windows are calculated by preprocessing. In case there is an overlap of time windows for start and finish, an activity must not finish before its start (10). This constraint can also be adapted to model a minimum processing time for activity i, i.e. a minimum life cycle length.

$$\left(x^s_{i,t} - x^s_{i,t-1}\right) \geq 0 \qquad \forall i \in I, t \in T^p_i \tag{6}$$

$$x^s_{i,t} \geq 1 \qquad \forall i \in I, t = \bar{s}_i \tag{7}$$

$$\left(x^f_{i,t} - x^f_{i,t-1}\right) \geq 0 \qquad \forall i \in I, t \in T^p_i \tag{8}$$

$$x^f_{i,t} \geq 1 \qquad \forall i \in I, t = \bar{f}_i \tag{9}$$

$$\left(x^s_{i,t} - x^f_{i,t}\right) \geq 0 \qquad \forall i \in I, t \in T \mid \underline{f}_i \leq t \leq \bar{s}_i \tag{10}$$

The next set of constraints deals with the ramp-up of variants. If a model is to be produced, it has to be offered in at least one variant (11). Variants can only be produced if the corresponding model is produced, i.e. between model start (12) and finish (13). If a variant is to be produced, exactly one engine needs to be assigned to it (14). However, an engine can only be assigned if it is being produced (15).

$$\left(x^s_{v,t} - x^f_{v,t}\right) - \sum_{r\in I^r_v} \left(x^s_{r,t} - x^f_{r,t}\right) \leq 0 \qquad \forall v \in I^v, t \in T^p_v \tag{11}$$

$$x^s_{r,t} - x^s_{v,t} \leq 0 \qquad \forall v \in I^v, r \in I^r_v, t \in T^s_v \tag{12}$$

$$x^f_{r,t} - x^f_{v,t} \geq 0 \qquad \forall r \in I^v, r \in I^r_v, t \in T^f_v \tag{13}$$

$$\sum_{e\in I^e_r} \left(z^s_{e,r,t} - z^f_{e,r,t}\right) - \left(x^s_{r,t} - x^f_{r,t}\right) = 0 \qquad \forall r \in I^r, t \in T^p_r \tag{14}$$

Table 2
Notation.

Type	Notation	Description
Sets	I	activities $i \in I$
	I^e / $I^e_{r,t}$	engines $e \in I^e$, $\subset I$ / I^e assignable to variant $r \in I^r$ in $t \in T$, $\subset I^e$
	I^r / I^r_p / I^r_ν / I^r_t	variants $r \in I^r$, $\subset I$ / I^r at to be produced at $p \in O^p$ / I^r of model $\nu \in I^\nu$, $\subset I^r$ / I^r potentially produced in $t \in T$, $\subset I^r$
	I^ν / I^ν_l	models, $\subset I$ / I^ν of product line $l \in L$, $\subset I^\nu$
	I^d	derivative pair $(i, j) \in I^d$ with $i, j \in I^\nu$ and j being a derivative of i
	I^g	generation pair $(i, j) \in I^g$ with $i, j \in I^\nu$ and j being the subsequent generation of i
	O	all organizational units, $o \in O$
	O^l	product lines $l \in O^l$, $\subset O$
	O^p	plants $p \in O^p$, $\subset O$
	T	planning horizon $t \in T$
	T^a	calendar years within the planning horizon $a \in T^a$, $\subset T$
	T^s_i	valid start periods $T^s_i = \{\underline{s}_i, \ldots, \bar{s}_i\}$, for project $i \in I$, $\subset T$
	T^f_i	valid finish periods $T^f_i = \{\underline{f}_i, \ldots, \bar{f}_i\}$, for project $i \in I$, $\subset T$
	T^p_i	valid processing period $T^p_i = \{\underline{s}_i, \ldots, \bar{f}_i\}$, for project $i \in I$, $\subset T$
Parameters	$\underline{d}_i$ / $\bar{d}_i$	minimum / maximum duration of models $i \in I^\nu$ and engines $i \in I^e$
	$\underline{d}^t_{i,j}$ / $\bar{d}^t_{i,j}$	minimum / maximum target for time lag between model starts $(i, j) \in I^d$
	$\underline{f}_i$ / $\bar{f}_i$	earliest / latest finish of $i \in I$
	$\bar{n}^\nu_l$	maximum number of simultaneous model starts per period in product line $l \in O^l$
	$\bar{n}^r_{\nu,\tau}$	maximum number of variant starts in $\tau = \{0, \ldots, t^r_\nu\}$ periods after start of $\nu \in I^\nu$
	c^{co2+}_t	cost of CO_2 cap exceedance
	c^{dis-} / c^{dis+}	cost of negative / positive deviation from target time lag
	c^{sim+}	cost of positive deviation from target limit of simultaneous model starts
	c^{sal-}	cost of negative deviation from target sales
	c^{ove+}	cost of overtime
	t^r_ν	time span after start of model $\nu \in I^\nu$, in which the number of corresponding variant starts is restricted
	$\underline{e}_{r,t}$ / $\bar{e}_{r,t}$ / $e^+_{e,r,t}$	minimal emission of $r \in I^r$ in $t \in T$ / maximal allowed emission of $r \in I^r$ in $t \in T$ / additional emission of $r \in I^r$, if $e \in I^e_r$ is used in $t \in T$
	$\underline{q}_t$	minimum desired sales in $t \in T$
	$\bar{q}_{t,p}$	maximum capacity in $t \in T$ at $p \in P$
	$q^p_{r,t,s,f}$	preprocessed, forecasted sales of $r \in I^r$ in $t \in T$ for start $s \in T^s_r$ and finish $f \in T^f_r$
	$\underline{s}_i$ / $\bar{s}_i$	earliest / latest start of $i \in I$
Variables	$q_{r,t}$	sales of $r \in I^r$ in $t \in T$
	$q^e_{r,e,t}$	sales of $r \in I^r$ in $t \in T$ with engine $e \in I^e$
	$x^s_{i,t}$	$= 1$ if production of $i \in I$ starts in $t \in T^p_i$ or before, 0 otherwise
	$x^f_{i,t}$	$= 1$ if production of $i \in I$ finishes in $t \in T^p_i$ or before, 0 otherwise
	$x^p_{r,t,t'}$	$= 1$ if production of $r \in I^r$ starts in $t \in T^p_r$ and finishes in $t' \in T^p_i$, 0 otherwise
	$z^s_{e,r,t}$	$= 1$ if assignment of $e \in I^e_r$ to $r \in I^r$ starts in $t \in T^p_{e,r}$ or before, 0 otherwise
	$z^f_{e,r,t}$	$= 1$ if assignment of $e \in I^e_r$ to $r \in I^r$ finishes in $t \in T^p_{e,r}$ or before, 0 otherwise
	$\Delta^{dis-}_{i,j} / \Delta^{dis+}_{i,j}$	negative or positive deviation from desired time lag for $(i, j) \in I^d$
	$\Delta^{sim+}_{l,t}$	deviation from a desired limit of simultaneous model starts for $l \in O^l$ in $t \in T$
	Δ^{sal-}_t	negative deviation from target sales in $t \in T$
	$\Delta^{ove+}_{t,p}$	overtime at $p \in O^p$ in $t \in T$
	Δ^{co2+}_a	exceedance of allowed emission in $a \in T^a$

Table 3
Activity status as a function of the variables.

Status	Expression		
Activity i has not yet started in period t	$x^s_{i,t}$	$\overset{!}{=}$	0
Activity i starts in period t	$x^s_{i,t} - x^s_{i,t-1}$	$\overset{!}{=}$	1
Activity i is processed in period t	$x^s_{i,t} - x^f_{i,t}$	$\overset{!}{=}$	1
Activity i finishes in period t	$x^f_{i,t} - x^f_{i,t-1}$	$\overset{!}{=}$	1
Activity i has been finished before period t	$x^f_{i,t-1}$	$\overset{!}{=}$	1

$$\left(z^s_{e,r,t} - z^f_{e,r,t}\right) - \left(x^s_{e,t} - x^f_{e,t}\right) \le 0 \qquad \forall r \in I^r, t \in T^p_r, e \in I^e_{r,t} \tag{15}$$

In the following, we present various constraints that further restrict start and finish times. For two successive generations of a model, a time lag of 0 holds, i.e. the finish of the previous generation equals the start of the next generation (16). Since our preprocessing ensures $T^f_i = T^s_j$ for all $(i, j) \in I^g$, we can simply formulate multiple constraints that enforce equality of start and finish variable for each period. Next, constraints (17) and (18) measure the deviation from the target distance between lead model and derivative. The length of model and engine lifecycles is restricted in (19) and (20), i.e. we enforce a specific time span between start and finish of corresponding activities. In (21), we measure the deviation from the target limit of simultaneous model starts per period and product line. Constraint (22) ensures a gradual variant ramp-up. If model $\nu \in I^\nu$ starts in period $t \in T^s_\nu$, we restrict the number of variant starts for periods $\tau \in [0, t^r_\nu]$.

$$x^f_{i,t} - x^s_{j,t} = 0 \qquad \forall (i, j) \in I^g, t \in T^f_i \tag{16}$$

$$\sum_{t \in T^s_j} t \cdot \left(x^s_{j,t} - x^s_{j,t-1}\right) - \sum_{t \in T^s_i} t \cdot \left(x^s_{i,t} - x^s_{i,t-1}\right) - \Delta^{dis+}_{i,j} \le \bar{d}^t_{i,j} \quad \forall (i, j) \in I^d \tag{17}$$

$$\sum_{t \in T^s_j} t \cdot \left(x^s_{j,t} - x^s_{j,t-1}\right) - \sum_{t \in T^s_i} t \cdot \left(x^s_{i,t} - x^s_{i,t-1}\right) + \Delta^{dis-}_{i,j} \ge \underline{d}^t_{i,j} \quad \forall (i, j) \in I^d \tag{18}$$

$$\sum_{t \in T^f_i} t \cdot \left(x^f_{i,t} - x^f_{i,t-1}\right) - \sum_{t \in T^s_i} t \cdot \left(x^s_{i,t} - x^s_{i,t-1}\right) \ge \underline{d}_i \quad \forall i \in \{I^\nu \cup I^e\} \tag{19}$$

$$\sum_{t \in T^f_i} t \cdot \left(x^f_{i,t} - x^f_{i,t-1}\right) - \sum_{t \in T^s_i} t \cdot \left(x^s_{i,t} - x^s_{i,t-1}\right) \le \bar{d}_i \quad \forall i \in \{I^\nu \cup I^e\} \tag{20}$$

$$\sum_{\nu \in I^\nu_l} \left(x^s_{i,t} - x^s_{i,t-1}\right) - \Delta^{sim+}_{l,t} \le \bar{n}^\nu_l \qquad \forall l \in O^l, t \in T \tag{21}$$

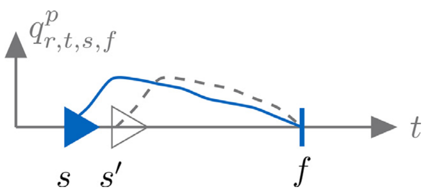


Fig. 3. Illustration of two different sales forecasts depending on SOP and EOP.

$$\sum_{r\in I^r_v}\left(x^s_{r,t+\tau}-x^s_{r,t+\tau-1}\right)-M\cdot\left(1-x^s_{v,t}+x^s_{v,t-1}\right) \le \bar{n}^r_{v,\tau} \quad \forall v\in I^v, t\in T^s_v, \tau\in[0,t^r_v] \tag{22}$$

Next, we describe sales $q_{r,t}$ as a function of SOP and EOP, i.e. $q_{r,t}$ is determined from a preprocessed, forecasted sales parameters $q^p_{r,t,s,f}$. Neglecting cannibalization and uncertainty, $q^p_{r,t,s,f}$ is the result of forecasting in the company and based on the knowledge of various domains [see e.g. 13]. As illustrated in Fig. 3, there is one forecasted sales curve for every valid combination of start s and finish f, captured in the parameter values for $q^p_{r,t,s,f}$. Depending on the chosen SOP and EOP for variant r, (27) assigns the corresponding vector of forecasted sales to $q_{r,t}$. For this we make use of the binary variable $x^p_{r,t,t'}$ which equals 1, if variant r is planned to have SOP t and EOP t'. This is ensured by (23) and (24), which only allow $x^p_{r,t,t'} > 0$ for a start or finish in t respectively t' as well as (25), which forces $x^p_{r,t,t'} = 1$ for the correct combination of t and t'. While the combination of constraints (23)–(25) is sufficient to ensure a correct value of $x^p_{r,t,t'}$, constraint (26) is included to improve performance. As a result of these constraints, $q_{r,t}$ is fully defined by summing up over all possible combinations of start and finish multiplied with the preprocessed, forecasted sales quantity $q^p_{r,t,s,f}$ (27). Summing up over all variants that are potentially produced in each period t, we can calculate the deviation from a desired target sales (28) as well as overtime at plants (29). Both parameters $\underline{q}_t$ and $\bar{q}_{p,t}$ typically are increasing in t.

$$x^p_{r,t,t'}-\left(x^s_{r,t}-x^s_{r,t-1}\right)\le 0 \qquad \forall r\in I^r, t\in T^s_r, t'\in T^f_r \tag{23}$$

$$x^p_{r,t,t'}-\left(x^f_{r,t'}-x^f_{r,t'-1}\right)\le 0 \qquad \forall r\in I^r, t\in T^s_r, t'\in T^f_r \tag{24}$$

$$\left(x^s_{r,t}-x^s_{r,t-1}\right)+\left(x^f_{r,t'}-x^f_{r,t'-1}\right)-x^p_{r,t,t'}\le 1 \qquad \forall r\in I^r, t\in T^s_r, t'\in T^f_r \tag{25}$$

$$\sum_{t\in T^s_r}\sum_{t'\in T^f_r}x^p_{r,t,t'}=1 \qquad \forall r\in I^r \tag{26}$$

$$q_{r,t}-\sum_{t'\in T^s_r}\sum_{t''\in T^f_r}\left(q^p_{r,t,t',t''}\cdot x^p_{r,t',t''}\right)=0 \qquad \forall r\in I^r, t\in T^p_r \tag{27}$$

$$\sum_{r\in I^r}q_{r,t}+\Delta^{sal-}_t\ge \underline{q}_t \qquad \forall t\in T \tag{28}$$

$$\sum_{r\in I^r_p}q_{r,t}-\Delta^{ove+}_{t,p}\le \bar{q}_{t,p} \qquad \forall t\in T, p\in O^p \tag{29}$$

Finally, in the last set of constraints, we measure the CO_2 cap exceedance as presented in the introduction, i.e. neglecting phase-in effects. The “allowed CO_2 emission” can be modelled as a resource overload constraint for which neither the demand nor the availability is fixed in advance. Following EU legislation, resource demand is the sales-weighted average of the portfolio emission while resource availability depends on the sales-weighted average of the portfolio weight. Generally this leads to a non-linear resource overload constraint as stated in (30). However, in preprocessing it is already possible to compute the allowed emission of each individual variant as well as the emission resulting from each engine assignment. Following a standard linearization approach [e.g. 35], constraints (31)–(33) map the sales quantity of a variant in a period $q_{r,t}$ to the engine assigned in this period. Consequently, only the assigned engine has $q^e_{e,r,t} > 0$ and we can calculate the aggregated deviation from the emission target. To reduce the number of big-M constraints in our model, this linearization is only done for those engine assignments that lead to higher emissions than $\underline{e}_{r,t}$. In consequence, constraint (34) calculates the actual emission of all variants as combination of the minimum emission per variant plus the additional emission of non-optimal engines.

$$\sum_{t\in T^a}\sum_{r\in I^r_t}\sum_{e\in I^e_{r,t}}\left(e_{e,r}-\bar{e}_{r,t}\right)\cdot q_{r,t}\cdot\left(z^s_{e,r,t}-z^f_{e,r,t}\right)-\Delta^{co2+}_a\le 0 \forall a\in T^a \tag{30}$$

$$q^e_{r,e,t}-M\cdot\left(z^s_{e,r,t}-z^f_{e,r,t}\right)\le 0 \qquad \forall r\in I^r, t\in T^p_r, e\in I^e_{r,t} \tag{31}$$

$$-q_{r,t}+q^e_{e,r,t}\le 0 \qquad \forall r\in I^r, t\in T^p_r, e\in I^e_{r,t} \tag{32}$$

$$q_{r,t}-q^e_{e,r,t}+M\cdot\left(z^s_{e,r,t}-z^f_{e,r,t}\right)\le M \qquad \forall r\in I^r, t\in T^p_r, e\in I^e_{r,t} \tag{33}$$

$$\sum_{t\in T^a}\sum_{r\in I^r_t}\sum_{e\in I^e_{r,t}}\left[\left(\underline{e}_{r,t}-\bar{e}_{r,t}\right)\cdot q_{r,t}+e^+_{e,r,t}\cdot q^e_{e,r,t}\right]-\Delta^{co2+}_a\le 0 \forall a\in T^a \tag{34}$$

3.2. Solution approach

Our model can be embedded in a rolling horizon. We differentiate the planning horizon in three different parts as illustrated in Fig. 4. First, we use a frozen horizon that contains models which had their SOP in the past or will have it in the very near future (typically less than five years). Even if models have their SOP in the frozen horizon, their EOP might still be an open decision. Second, we have a detailed planning part in which models, engines, and variants are scheduled. Third, we have an initial planning part, in which model introductions are scheduled, but engines and variants are not considered yet. Applying this model in a rolling horizon leads to regular updates of both input data and decisions. Modifications in the input data could for instance relate to updates in the forecasted sales as well as changes of the portfolio or the product plant allocation.

In general, our model can be considered as a goal programming approach, where deviations from desired target levels are minimized. In order to focus on the goal deviations, constant cost coefficients of one unit are assumed for all objectives. Thereby, we are only interested in pareto-optimal, i.e. non-dominated solutions. These solutions are identified via lexicographic ordering and the ϵ-constraint method, two well established multi-criteria optimization methods as reviewed by Ehrgott [36].

When exploring the solution space, we differentiate between externally given goals and managerial goals. As the CO_2 cap limit is given externally and cannot be influenced, it has a higher priority than the remaining managerial goals Δ^{dis}, Δ^{sim}, Δ^{sal}, and Δ^{ove}. In consequence, we use lexicographic ordering to first minimize the CO_2 cap exceedance and restrict the solution space to the minimal CO_2 cap exceedance, before exploring trade-offs between the remaining goals. Note that we are still able to investigate the impact of the CO_2 cap by executing the subsequent steps twice, with

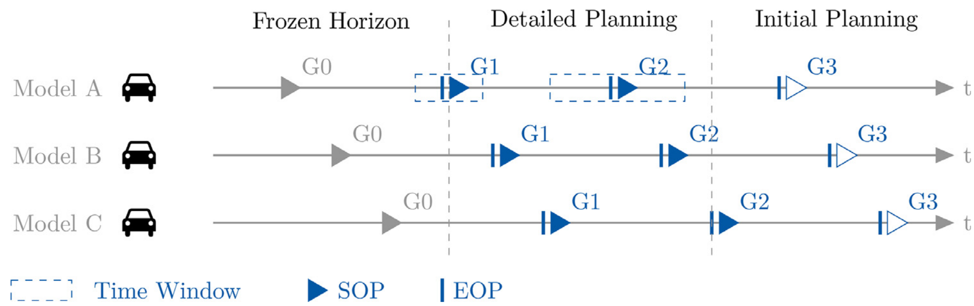


Fig. 4. The current project schedule is to be extended in a rolling horizon scheme.

and without restricting the feasible region to the minimal CO_2 cap exceedance.

To efficiently explore trade-offs between the four remaining goals, we first determine the feasible region that may actually entail trade-offs. For this we determine all extreme solutions by solving all permutations of the lexicographically ranked goals.

In the model presented in the previous section, managerial goals are not restricted via additional hard constraints. Depending on the problem instance, it may however be necessary to restrict the time lag between derivatives or the resource consumption per period. Adding such constraints is straightforward and may be part of what-if analyses.

4. Numerical study

In the following, we first characterize the baseline data set including the definition of the goals. Starting from this baseline data set, we report the results of a computational study in which we analyze the performance of our model for both the baseline data set and variations of this data set.

4.1. Test instance

For our case study, a data set has been created in cooperation with a major European automotive company. As a detailed planning horizon, we consider the years from 2015 until 2021, i.e. the frozen horizon ends in 2015 and variants need to be planned until 2021.

The portfolio considered consists of almost 150 models and 150 engines, from which 500 variants have to be created. Please note, the exact numbers of models and engines are not necessarily identical. Not every engine can be used in every model, but variants can be build with multiple engines. As one of our aims is to analyze the influence of the cap limit on CO_2 emission imposed by the European Union, we decided to only consider forecasted sales data for the European Market, which we received from our case company. This data covers the years 2015–2021 and was provided in 2015. Due to reasons of confidentiality, the portfolio structure used in this test instance is only based on products that are publicly known until 2018. Hence, our data set does not contain any information about how the portfolio will change afterwards. In consequence, we neither removed current products nor added new products. Instead, a next generation product has been defined for each product available on the market until 2018, to ensure that the dataset has future product introductions to plan. For each model, engine, and variant we defined realistic time windows as described in the previous section.

Since we only consider forecasted sales data for the European market while plants are shared for world-wide demand, we adjusted plant capacities to the European share of the demand accordingly.

Table 4
Data sets for the computational study (including baseline data set D2).

Data	Planning Horizon	Variants	Max size T_i^s	Max size T_i^f
D1	2015–2018	377	7	27
D2	**2015-2021**	**453**	**7**	**28**
D3	2015–2018	388	13	33
D4	2015–2021	471	13	33
D5	2015–2021	337	7	28
D6	2015–2021	111	7	25

While we were able to use real-world data for the portfolio structure as well as corresponding forecasted sales data, we had to simplify the data for CO_2 emission of engines assigned to variants due to two reasons. First, CO_2 emissions also depend on other factors than only on the engine assignment. Second, our model allows to assign engines to variants that have never been developed and sold in that combination before. Hence, the company is not able to provide data for all potential engine-variant combinations. However, we are able to use realistic data for our emissions. Instead of simply using average data, we created a linear regression model from real-world data. Our regression model is build on more than 120 observations and has an R^2 of 88%. In a stepwise linear regression approach, we defined the following variables for our regression model: variant weight, engine size, fuel type, chassis type, sport's edition, and year of the last update. Assuming that the company always assigned the latest engines, the year of last update serves as a proxy for the yearly efficiency improvement, i.e. reduced emission due to technological progress.

In general, our goals are defined as described by the objective functions and corresponding constraints in the previous section. Goal deviations on the model level, i.e. Δ^{dis} and Δ^{sim}, are measured for the entire planning horizon excluding the frozen horizon. In contrast, goal deviations on the variant level, i.e. Δ^{sal}, Δ^{ove} and Δ^{co2}, are only measured for the detailed planning horizon. Furthermore we measure entire calendar years, i.e. if the frozen horizon or the detailed planning horizon ends in the middle of a calendar year, we still measure the entire year.

4.2. Computational study

To study the computational performance of our model, we solve the baseline data set and several variations as summarized in Table 4 (in which the baseline data set is D2). The variations include different sizes of time windows, different lengths of the planning horizon, and number of variants. Due to the inherent logic of our planning problem, it is not possible to fully isolate these variations. For instance, the number of variants to be considered is indirectly influenced by both the size of the time windows and the length of the planning horizon. Hence, instead of trying to isolate individual modifications, we ensured that the general structure of our data set is maintained.

Table 5
Impact of the number of goals on the computation time.

Data set	Minimal Δ^{co2}	Avg (and SD) Computation Time [s]			
		1 Goal	2 Goals	3 Goals	4 Goals
D1	yes	8 (5)	195 (482)	1,016 (1,496)	2,355 (1,626)
	no	2 (1)	81 (187)	812 (1,292)	1,830 (1,692)
D2	yes	66 (46)	98 (54)	250 (385)	299 (299)
	no	28 (37)	351 (962)	921 (1,414)	1,072 (1,429)
D3	yes	10 (3)	24 (17)	598 (1,073)	3,114 (946)
	no	4 (2)	14 (11)	258 (725)	2,545 (1,555)
D4	yes	75 (26)	102 (33)	162 (66)	253 (174)
	no	47 (77)	553 (1,079)	1,109 (1,385)	2,297 (1,543)
D5	yes	48 (28)	55 (33)	88 (51)	47 (28)
	no	3 (11)	41 (76)	602 (1,073)	805 (1,366)
D6	yes	5 (1)	5 (1)	8 (5)	8 (6)
	no	1 (1)	4 (8)	4 (3)	6 (6)

Table 6
Impact of the number of goals on the optimality gap.

Data set	Minimal Δ^{co2}	Avg (and SD) Optimality Gap [%]			
		1 Goal	2 Goals	3 Goals	4 Goals
D1	yes	0.0 (0.0)	0.0 (0.0)	1.7 (5.4)	9.1 (15.7)
	no	0.0 (0.0)	0.0 (0.0)	0.8 (4.0)	5.63 (10.7)
D2	yes	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	no	0.0 (0.0)	0.0 (0.0)	0.6 (2.0)	1.6 (3.5)
D3	yes	0.0 (0.0)	0.0 (0.0)	0.1 (0.5)	20.1 (26.4)
	no	0.0 (0.0)	0.0 (0.0)	0.1 (0.3)	3.4 (4.7)
D4	yes	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	no	0.0 (0.0)	0.0 (0.1)	3.7 (11.8)	14.3 (23.7)
D5	yes	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	no	0.0 (0.0)	0.0 (0.0)	0.8 (3.3)	0.9 (3.3)
D6	yes	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	no	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)

Table 7
The impact of the number of goals on the model size.

# Goals	∅ Rows [%]	∅ Columns [%]	∅ Non-Zeros [%]
1	100	100	100
2	127	127	162
3	130	130	205
4	132	133	251

Tables 5 and 6 give the results of the determination of extreme points as described in Section 3.2. In each table, the second column shows, if the CO_2 cap is considered or not. Columns 3 - 6 report the computations times (in Table 5) and the optimality gap (in Table 6), if one to four managerial goals are considered. For our numerical analysis, all models are solved with Gurobi 8.0 with a time limit of 3,600 s and Gurobi's default optimality gap of 0.01%.

The more managerial goals are considered as either objective or constraint, the higher the average computation time is (Table 5). The average model size also increases with the number of goals as summarized in Table 7. If the CO_2 cap exceedance is minimized for an instance including the years 2020 and 2021 for detailed planning, the computation time is lower than for instances in which emission is not considered. This is because for considering the CO_2 cap first, the model minimizes sales of those variants that would otherwise lead to a CO_2 cap exceedance and thereby reduces the solution space considerably. Finally, our results show that the computation is relatively robust against the length of the planning horizon, but strongly affected by time window size and the number of variants.

While most models can be solved to optimality, there are five model executions with a high relative optimality gap > 30%. In four of these five executions, the objective was to minimize Δ^{sim} as a fourth goal leading to absolute deviations ≤ 6. Generally, the size of the optimality gap (Table 6) correlates with the length the computation time, i.e., instance goal combinations with a large optimality gap tend to require long computation times and vice versa.

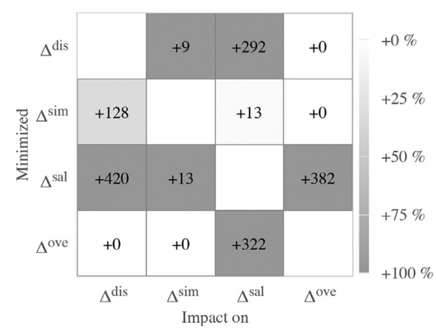


Fig. 5. Lexicographic trade-off between two goals (cell label = absolute, cell color = relative).

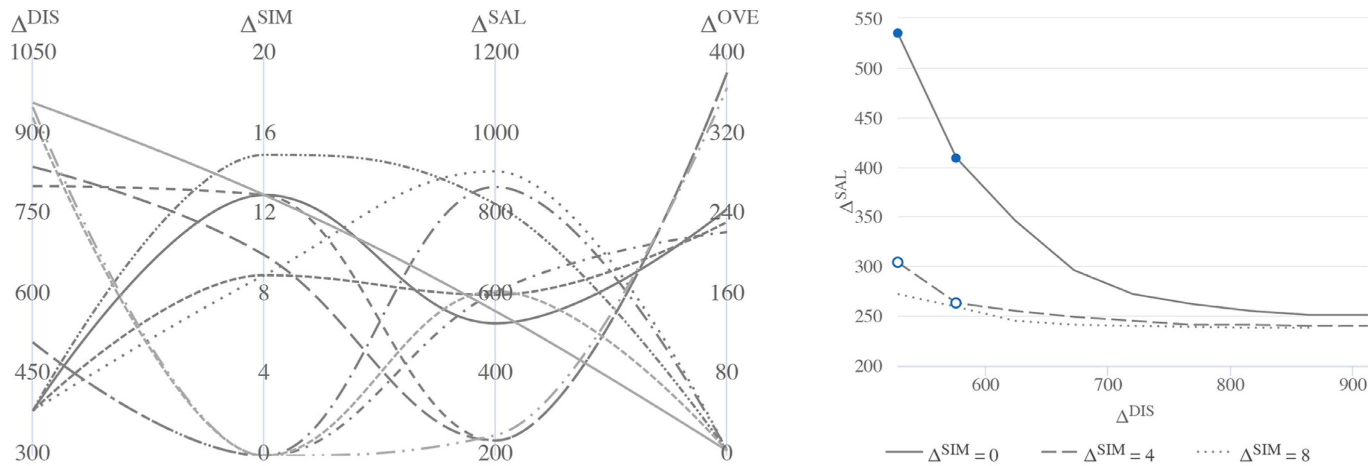
5. Managerial insights

5.1. Minimal goal deviations and goal trade-offs

To begin with, we analyze minimum goal deviations for all goals individually. While we are able to obtain solutions without any goal deviation for Δ^{sim} and only a minor deviation of Δ^{ove} = 5k units, we are not able to reach the target level for Δ^{dis} = 384 months, Δ^{sal} = 238k units, and Δ^{co2} = 26 tons. The implications of Δ^{co2} and necessary changes to achieve the required target level for the CO_2 cap limit are discussed in the next subsection. For illustrative purposes, the remainder of this subsection, is focused on the interaction between managerial decisions, without considering CO_2.

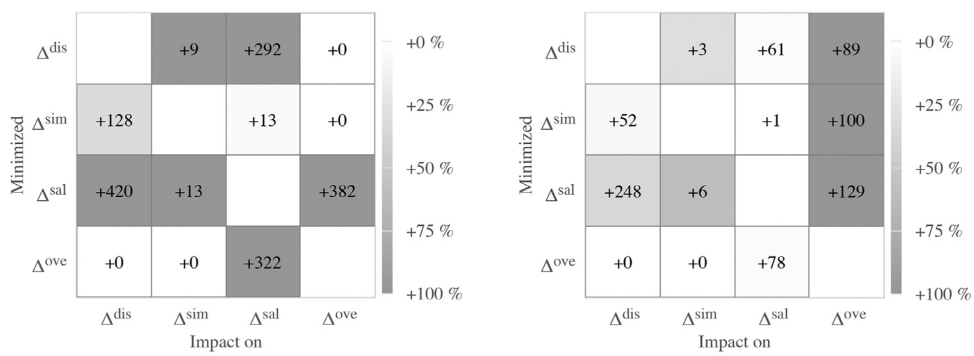
Even though we find a solution with $\Delta^{sim} = 0$, i.e. a schedule without any parallel model SOPs, the corresponding goal is still challenging for the company. Once other goals are being considered and we are searching for pareto-optimal solutions, there is typically a trade-off between corresponding goals. Fig. 5 illustrates the impact of each managerial goal on each other goal. More precisely, this matrix is to be interpreted as "row impacts column". For instance, if we first minimize Δ^{dis} (row), then Δ^{sim} (column) increases by 9 simultaneous SOPs which translates into a relative increase ≥ 100% and is colored accordingly.

After lexicographically optimizing all permutations of goal sequences, we obtain the extreme points of the pareto-optimal solutions (Fig. 6a). The interpretation of this parallel coordinates chart [37] is as follows: There is one axis per goal and one curve per pareto-optimal solution. The intersection of a solution curve and an axis represents the goal deviation of this solution with re-



(a) Lexicographic Ordering (b) Epsilon Constraint

Fig. 6. Trade-offs need to be addressed in the interest of the overall company.



(a) Without Emission (b) With Emission

Fig. 7. Impact of emission on the pareto surface (cell label = absolute, cell color = relative).

spect to the goal given on the axis. In general, we observe a wide range of optimal values for the individual goals. While less obvious for Δ^{dis} and Δ^{sim}, there is a clear trade-off between Δ^{sal} and Δ^{ove}.

To study the impact of Δ^{dis} and Δ^{sim} in more detail, the ϵ-constraint method is applied. For illustrative purposes, the interaction between Δ^{dis}, $\Delta^{sim}$and Δ^{sal} is presented in Fig. 6b. If $\Delta^{sim} = 0$, we can observe that a change in Δ^{dis} from 528 to 576 months (+9 %) leads to a reduction in Δ^{sal} from 535k to 409k units (-24%). Although still observable, this effect is much weaker for higher values of Δ^{sim}. Furthermore, it can be seen that Δ^{sal} generally decreases with increasing Δ^{dis} or Δ^{sim}.

5.2. Impact of the CO_2 limit

Without considering any other goal, the minimal exceedance of the CO_2 cap is 26 tons, whereby deviations only occur in 2020 and 2021. If the CO_2 cap exceedance is restricted to the minimal value of 26 tons before exploring managerial trade-offs, the changes to the pareto-optimal solutions are illustrated in Fig. 7. For instance, while Δ^{dis} and Δ^{sim} had no impact on Δ^{ove} in Fig. 7a, Δ^{ove} is strongly influenced by all goals in Fig. 7b. In contrast, Δ^{dis}, Δ^{sim} and Δ^{sal} are less sensitive to the other goals in Fig. 7b.

However, the pareto surface does not only change it's shape, but also the range of individual goal deviations. As illustrated in Fig. 8a to b, most goal deviations are higher and all goal deviation ranges become smaller. The smaller ranges imply a reduced degree of freedom for the decision maker. This observation is in line with Fig. 8c, where it is visible that the model tries to minimize sales from 2020 onward, as the current yearly efficiency improvement is not sufficient to compensate for the reduction of the CO_2 cap in 2020. Without further improvements of the efficiency, high penalties will occur from 2020 onward. Even if sales is reduced, such a penalty can amount to more than 1 billion for the baseline data set.

As our case company is obviously not able to fulfill its goals with the current trend in efficiency improvement per year, additional measures have to be developed in order to comply with the reduced cap limit from 2020 onwards. In general, various courses of action can be evaluated with our model. First, the company can determine the required yearly efficiency improvement rate, i.e. how much the CO_2 emission of the model portfolio has to be reduced each year. Based on our regression model, the current improvement rate is about 1 gram per year. Iteratively increasing the yearly efficiency improvement, it turns out that a total of 7 gram per year is required to compensate for the reduced cap limit (see dotted line in Fig. 8). Starting from an average emission of 130 g/km, this increased efficiency improvement translates into a yearly CO_2 reduction of about 5 %. Second, the company can analyze the impact of technical changes on those models that are sold in a particular high quantity or have a particular high emission. Third, the company can reduce the emission of its model portfolio by offering hybrid or fully electrical models. Within the scope of this paper, it is not possible to fully evaluate and compare these courses of action since other types of emission, (e.g. NO_x), financial aspects as well as cannibalization among different products would have to be taken into account. However, in the following we dis-

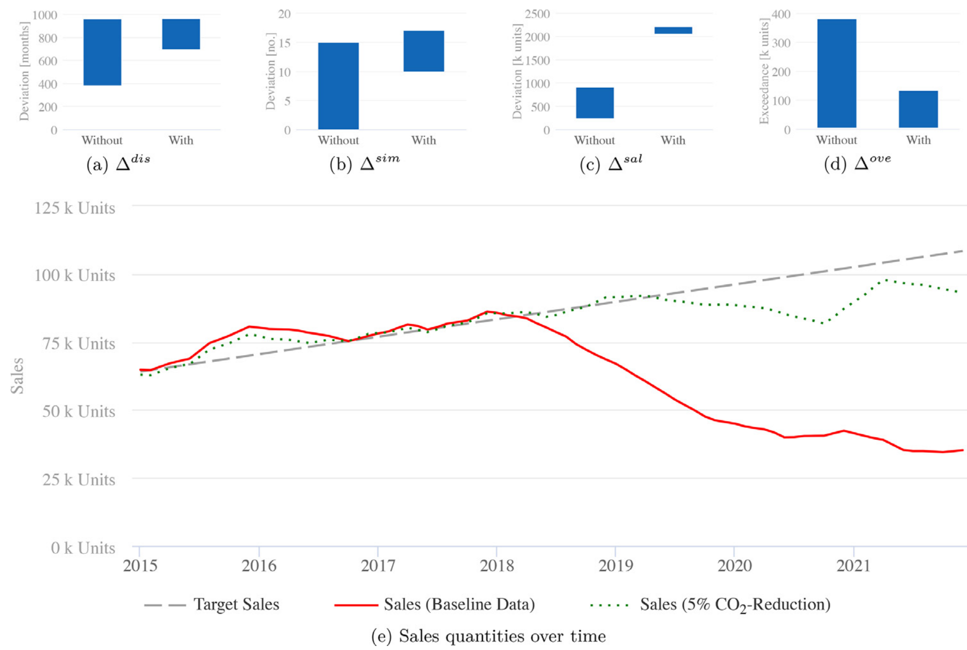


Fig. 8. The impact of emission on other goals.

Table 8
Minimal Δ^{sal} [k units] for yearly efficiency improvement and target growth rates (compared to the baseline data).

Efficiency Improvement [$\frac{g}{year}$]	Target Growth Rate [$\frac{\%}{year}$] 5 Δ^{sal}	(%)	10 Δ^{sal}	(%)	15 Δ^{sal}	(%)	Avg Δ^{sal}	(%)
0.5	2,269.3	(+ 10)	3,200.0	(+ 56)	4,134.0	(+ 101)	3,201.1	(+ 56)
1.0	1,346.0	(- 35)	2,056.1	(N/A)	2,823.3	(+ 37)	2,075.1	(+ 1)
1.5	0.0	(- 100)	238.2	(- 88)	1,021.7	(- 50)	420.0	(- 80)
Avg	1,205.1	(- 41)	1,831.4	(- 11)	2,659.7	(+ 29)		

cuss three different perspectives with respect to their impact on meeting the CO_2 cap limit.

First, we study the interaction of the yearly efficiency improvement and the yearly target growth rate on Δ^{sal}. To this end, we altered both the yearly efficiency improvement and the target growth rate. Starting from our baseline data (1.0 gram per year and 10 % per year), each parameter was multiplied with either 50 % or 150 % leading to eight different modifications. The result of this analysis is summarized in Table 8. For each modification we report the resulting Δ^{sal} as well as the relative change of Δ^{sal} compared to the baseline with an efficiency improvement of 1.0 gram per year and a target growth rate of 10 % per year. Since averages in the last column range from −80 % to +56 % while averages in the last row range from −41 % to +29 %, we can conclude that the yearly efficiency improvement has a higher impact on Δ^{sal} than the yearly target growth rate. Furthermore, we see that the sales target can only be met with an increased efficiency of 1.5 gram per year and a reduced growth rate of 5 % per year.

Second, we consider that in recent years, an increasing demand for sport utility models (SUVs) has been observed. To test the impact of a continued increase in demand for SUVs, we double the forecasted sales parameter $q_{r,t,s,f}$ for all SUV-variants that are sold

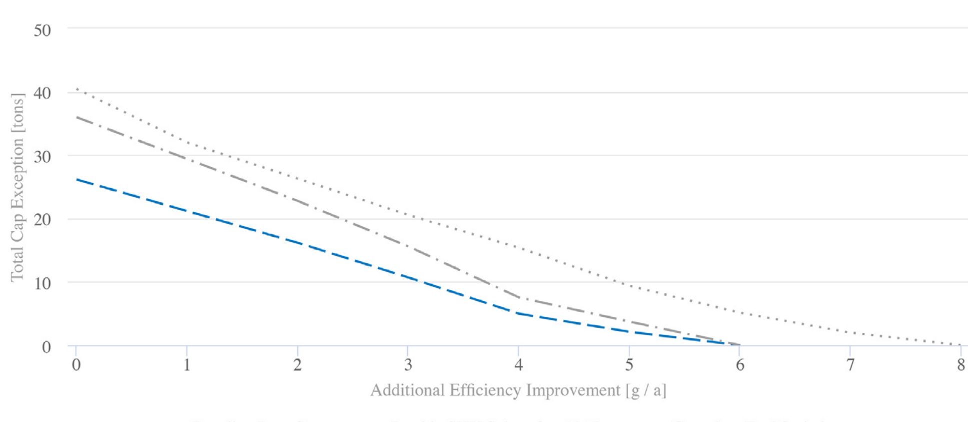


Fig. 9. Total amount of emissions above the CO_2 cap as a function of additional efficiency improvement.

after the frozen horizon (after 2015). This modification not only changes the sales of specific models that have a relatively high CO_2 emission, but also changes the total sales in each period. As visible in Fig. 9, the deviation from the allowed CO_2 emission is generally higher if the demand for SUVs is higher. However, with an additional yearly efficiency improvement of 6 gram per year (similar to the baseline case), we are able to find a solution that does not exceed the limit of CO_2 emission while it completely fulfills target sales in each period.

Third, inspired by the current trend to move away from diesel engines, we tested the impact of all customers switching from diesel to gasoline. According to our regression model, the CO_2 emission of diesel variants is nearly 20 g below the emission of gasoline variants. To simulate a scenario, in which all customers switch from diesel to gasoline, we simply remove the efficiency advantage of diesel engines in our preprocessing, i.e. we still assign diesel engines but increase $e_{r,t}$. In contrast to the previous modification, sales remains unchanged in this scenario. Again, the cap exceedance generally increases compared to our baseline data set as illustrated in Fig. 9. However, the required efficiency improvement to compensate for the reduced cap limit on CO_2 emission increases from 6 gram per year to 8 gram per year (+33%). Increasing efforts in efficiency improvement would thus be required to stay within the CO_2 cap.

6. Conclusions

In this paper, a new model for the strategic planning of platform-based product introductions has been presented. As a theoretical contribution, this model captures the planning problem as presented in Section 1 by integrating scheduling, platform-planning, and resource leveling as a multi-objective optimization problem. Unlike classical optimization models in the resource leveling problem, we treat start and finish as separate decisions. Depending on the decision of start and finish, our model allows to load different parameters for sales, i.e. resource demand. Like this, it allows to analyze key trade-offs in strategic planning of new product introductions.

As a practical contribution, our model serves decision makers in various tasks of strategic planning as a sound methodological basis. It not only increases the awareness for pareto-optimal solutions and corresponding trade-offs, but also allows for the evaluation of various courses of action. Instead of investing time in the design of solutions, decision makers can focus on the detailed evaluation and comparison of promising solutions. In consequence our model promises a significant increase in both effectiveness and efficiency of strategic planning. Effectiveness increases since our model specifically searches for pareto-optimal solutions. Efficiency increases as more solutions can be evaluated in shorter time. The latter is of special importance in times of technological change, e.g. during the current transition to an electrified model portfolio.

Due to the characteristics of our modeling approach, some effects such as sales cannibalization or phase-in effects in the CO_2 regulation would require additional linearization and are hence not easy to integrate. However, our model allows the consideration of some of the most relevant goals for strategic planning and enables decision makers to analyze various modifications of the input data such as different technology roadmaps or different sales forecasts.

Future research could focus on both modeling aspects and considerations related to the solution procedure. In order to exploit the full potential of our model, an improved approach to incorporating estimated sales figures could be studied. This approach could address for instance cannibalization, but possibly also develop ways to deal with uncertainty and lead to robust solutions. Next, to analyze the impact of the distribution of costs over time, a relevant question is to what extent goal deviations in the far future can be discounted in favor of reducing goal deviations in the near future. Eventually the model can be extended in various ways. Based on improved sales data it seems promising to analyze financial impacts in more detail. Useful applications are the influence of strategic schedules on the maximization of net present value as well as the minimization of fluctuations in the overall contribution margin. Furthermore, the integration of platform planning could be extended by modeling more advanced product-module relationships such as mode identity [38] as well as the compatibility of different module types. Finally, with respect to the solution procedure, the development of a heuristic could also be considered. Even though our model is able to cope with reasonably-sized problem instances, a heuristic solution procedure might allow for a more interactive, real-time use of the model.

Declaration of Competing Interest

None.

References

[1] Fogliatto FS, da Silveira GJ, Borenstein D. The mass customization decade: an updated review of the literature. Int J Prod Econ 2012;138(1):14–25. doi:10.1016/j.ijpe.2012.03.002.
[2] Robertson D, Ulrich KT. Planning for product platforms. Sloan Manage Rev 1998;39(4):19–31.
[3] Vickery SK, Koufteros X, Dröge C, Calantone R. Product modularity, process modularity, and new product introduction performance: does complexity matter? Prod Oper Manage 2016;25(4). doi:10.1111/poms.12495.
[4] Galizia FG, ElMaraghy H, Bortolini M, Mora C. Product platforms design, selection and customisation in high-variety manufacturing. Int J Prod Res 2020;58:839–911. doi:10.1080/00207543.2019.1602745.
[5] Wochner S, Grunow M, Staeblein T, Stolletz R. Planning for ramp-ups and new product introductions in the automotive industry: extending sales and operations planning. Int J Prod Econ 2016;182:372–83. doi:10.1016/j.ijpe.2016.07.008.
[6] Volpato G, Stocchetti A. Managing product life cycle in the auto industry: evaluating carmakers effectiveness. Int J Automot TechnolManage 2008;8(1):22. doi:10.1504/IJATM.2008.018766.
[7] Becker A, Stolletz R, Stäblein T. Strategic ramp-up planning in automotive production networks. Int J Prod Res 2017;55(1):59–78. doi:10.1080/00207543.2016.1193252.
[8] European Parliament. Regulation (EC) No 443/2009 of the European parliament and council setting the emission performance standards for new passenger cars as part of the Communicty's integrated approach to reduce CO2 emission from light-duty vehicles. 2009.
[9] Zhou X, Wei X, Lin J, Tian X, Lev B, Wang S. Supply chain management under carbon taxes: a review and bibliometric analysis. Omega 2021;98. doi:10.1016/j.omega.2020.102295.
[10] Sadeghi A, Alem-Tabriz A, Zandieh M. Product portfolio planning: a metaheuristic-based simulated annealing algorithm. Int J Prod Res 2011;49:2327–50. doi:10.1080/00207540903329338.
[11] Wilson LO, Norton JA. Optimal entry timing for a product line extension. Mark Sci 1989;8:1–17.
[12] Norton JA, Bass FM. A diffusion theory model of adoption and substitution for successive generations of high-technology products. Manage Sci 1987;33:1069–86.
[13] Jiang Z, Jain DC. A generalized Norton-Bass model for multigeneration diffusion. Manage Sci 2012;58:1887–97. doi:10.1287/mnsc.1120.1529.
[14] Ramdas K. Managing product variety: an integrative review and research directions. Prod Oper Manage 2003;12:79–101. doi:10.1111/j.1937-5956.2003.tb00199.x.
[15] Zhang LL. A literature review on multitype platforming and framework for future research. Int J Prod Econ 2015;168:1–12. doi:10.1016/j.ijpe.2015.06.004.
[16] Abbas M, ElMaraghy H. Co-platforming of products and assembly systems. Omega 2018;78:5–20. doi:10.1016/j.omega.2018.01.005.
[17] Ben-Arieh D, Easton T, Choubey A. Solving the multiple platforms configuration problem. Int J Prod Res 2009;47(7):1969–88. doi:10.1080/00207540701561520.
[18] Van den Broeke M, Boute R, Cardoen B, Samii B. An efficient solution method to design the cost-minimizing platform portfolio. Eur J Oper Res 2017;259(1):236–50. doi:10.1016/j.ejor.2016.10.003.
[19] Kang CM, Hong YS, Huh WT. Platform replacement planning for management of product family obsolescence. IIE Trans 2012;44(12):1115–31. doi:10.1080/0740817X.2012.672791.
[20] Jana P, Graves SC, Grunow M. Balancing benefits and flexibility losses in platform planning. SSRN 2018:1–38. doi:10.2139/ssrn.3134037.
[21] Dash B, Gajanand MS, Narendran TT. A model for planning the product portfolio and launch timings under resource constraints. Int J Prod Res 2018;56:5081–103. doi:10.1080/00207543.2017.1394588.
[22] Thomé AMT, Scavarda LF, Fernandez NS, Scavarda AJ. Sales and operations planning: a research synthesis. Int J Prod Econ 2012;138(1):1–13. doi:10.1016/j.ijpe.2011.11.027.

[23] Tuomikangas N, Kaipia R. A coordination framework for sales and operations planning (S&OP): synthesis from the literature. Int J Prod Econ 2014;154:243–62. doi:10.1016/j.ijpe.2014.04.026.
[24] Fleischmann B, Ferber S, Henrich P. Strategic planning of BMW's global production network. Interfaces 2006;36(3):194–208. doi:10.1287/inte.1050.0187.
[25] Möhring RH. Minimizing costs of resource requirements in project networks subject to a fixed completion time. Oper Res 1984;32(1):89–120. doi:10.1287/opre.32.1.89.
[26] Gather T, Zimmermann J, Bartels JH. Exact methods for the resource levelling problem. J Sched 2011;14(6):557–69. doi:10.1007/s10951-010-0207-8.
[27] Rieck J, Zimmermann J. Exact methods for resource leveling problems. In: Schwindt C, Zimmermann J, editors. Handbook on project management and scheduling, vol. 1. Cham: Springer; 2015. p. 361–87. doi:10.1007/978-3-319-05443-8_17. ISBN 9783319054438
[28] Neumann K, Schwindt C, Zimmermann J. Project scheduling with time windows and scarce resources. Berlin: Springer; 2003. doi:101007/978-3-540-24800-2. ISBN 978-3-642-07265-9
[29] Mika M, Waligóra G, Weglarz J. Overview and state of the art. In: Schwindt C, Zimmermann J, editors. Handbook on project management and scheduling, vol. 1. Cham: Springer; 2015. p. 445–90. doi:10.1007/978-3-319-05443-8_21.
[30] Hartmann S. Project scheduling with resource capacities and requests varying with time: a case study. Flexible Ser Manuf J 2013;25(1-2):74–93. doi:10.1007/s10696-012-9141-8.
[31] Coughlan ET, Lübbecke ME, Schulz J. A branch-price-and-cut algorithm for multi-mode resource leveling. Eur J Oper Res 2015;245(1):70–80. doi:10.1016/j.ejor.2015.02.043.
[32] Rieck J, Zimmermann J, Gather T. Mixed-integer linear programming for resource leveling problems. Eur J Oper Res 2012;221(1):27–37. doi:10.1016/j.ejor.2012.03.003.
[33] Mellentien C, Schwindt C, Trautmann N. Scheduling the factory pick-up of new cars. OR Spect 2004;26(4):579–601. doi:10.1007/s00291-004-0174-6.
[34] Artigues C, Koné O, Lopez P, Mongeau M. Mixed-integer linear programming formulations. In: Schwindt C, Zimmermann J, editors. Handbook on project management and scheduling, vol. 1. Cham: Springer International Publishing; 2015. p. 17–41. doi:10.1007/978-3-319-05443-8_2.
[35] Williams HP. Model building in mathematical programming. 5th ed. Chichester: John Wiley & Sons; 2013. ISBN 978-1-118-44333-0
[36] Ehrgott M. Multicriteria optimization. Berlin: Springer; 2005. doi:101007/3-540-27659-9. ISBN 978-3-540-27659-3
[37] Inselberg A. The plane with parallel coordinates. Vis Comput. 1985;1(2):69–91. doi:10.1007/BF01898350.
[38] Salewski F, Schirmer A, Drexl A. Project scheduling under resource and mode identity constraints: model, complexity, methods, and application. Eur J Oper Res 1997;102(1):88–110. doi:10.1016/S0377-2217(96)00219-6.