Time-to-Market and Product Performance Tradeoff Revisited

Ali Yassine and Sally Souweid

***Abstract*—The profitability, and even the survival, of organizations depends on the number and quality of new products introduced into the market. However, the process of developing new products (and estimating the proper timing for their introduction into the market) remains a rich topic for research and investigation within the product development (PD) community as it lies at the intersection of the engineering and marketing disciplines. A unifying model that brings both engineering and marketing concerns together is necessary to bridge the gap between both disciplines. In this article, a mathematical model is introduced to study the tradeoff between product performance and time-to-market for different PD scenarios. These scenarios vary in three main aspects related to product characteristics (i.e., the product complexity and the product newness) and supply chain configuration (i.e., the degree of supplier involvement). The model aims to maximize the revenue of the firm over a limited marketing window. The optimal solution reveals interesting managerial insights regarding the time that must be spent on "system design" and on "detailed design" phases for each PD scenario.**

***Index Terms*—Modularity, product complexity, product development (PD), product newness, supplier involvement, system design.**

I. Introduction

AMID fierce competition that reigns most industries, firms are paying more attention to product development (PD) cycle-time, focusing on fast go-to-market and the advantages of being first to market [6]. In addition to fast time-to-market (i.e., short PD time), high product quality and performance also provide these firms with the necessary competitive advantage [57]. A quick product introduction into the market usually grants the firm a competitive advantage leading to a higher market share, longer product life, and a favorable cash flow [34]. However, this rushed introduction into the market, which is associated with a compressed PD process, can result in inferior product quality or performance (which has a negative effect on demand) [45], [49]. Numerous examples can be listed in this context. For instance, the rushed introduction of the Boeing 787 Dreamliner, which was packed with highly innovative technologies, resulted in several problems after delivery. These problems led the company to modify those units sold and incur substantial expenses [40]. Likewise, Mercedes introduced the small segment A class model car as a result of a development time reduced in half compared to previous models. During test driving of the new car, the problem of turning over at moderate speed was witnessed; this led the company to recall all cars for redevelopment at considerable incurred costs [33]. In 2016, Samsung rushed Galaxy Note 7 to the market in order to outdo rivals, however after reports of exploding batteries and overheating, Samsung was obliged to recall more than 3 million items sold and halt the production of the smartphone model [41]. In fact, a product recall is associated with significant incurred costs including litigation fees, defects repairing and the cost of sales loss [1]. On the other hand, as the product performance is considered an essential contributor to the product success in the market and a promoter of high profitability, some firms tend to spend too much time on improving the quality of the product and end up missing a limited window of opportunity [32]. Nike FuelBand, for instance, was launched when the market became saturated with fitness devices wrist band, such as Fitbit, Apple watches, and Garmins [4]. Similarly, Microsoft Zune failed to compete with the iPod due to its late introduction into the market following a prolonged development process [4]. The challenge in compressing the PD process time is not to cut corners, but to carefully accomplish the development tasks without sacrificing the quality or performance of the developed product [48], [50].

The time-to-market versus product performance tradeoff has been the subject of numerous studies. Early work by [13] introduced a mathematical model of a multistage PD process that captured the tradeoff between the time-to-market and the new product quality. The model illustrates how the optimal time-to-market and product performance vary with several factors, such as the size of the potential market, the presence of existing products, the profit margins, the duration of the opportunity window, the speed of product improvement, and the competitor's product performance. The analysis of this model concluded that when the product quality improvement is additive, it is optimal to focus efforts on the most productive stage of the PD process [13].

Similarly, Bayus [8] formulated a mathematical model to examine the time-to-market and product performance tradeoff. His approach is based on the relationship between the cost incurred in compressing the new PD process and the revenues generated as a function of the performance level and the window of market opportunity. In the event of a firm intending to catch a

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The authors are with the Department of Industrial Engineering and Management, American University of Beirut, Beirut 1107 2020, Lebanon (e-mail: sns17@mail.aub.edu; ay11@aub.edu.lb).

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competitor that has just introduced a new product to the market, the model suggests, a quick launch of a low performance product when the window of opportunity is short, the competitor is weak and the firm's development costs are high. In case a firm is seeking to outperform its rival, the model suggests being first to market with a high product performance when the window of opportunity is long, the sales are high, and the margins are stable.

Product reliability was also used in the time-to-market tradeoff [3]. This article showed the conditions where a company has incentives to release a less reliable product (e.g., a buggier software) early and patch it later in a larger market. Also, Ozer and Uncu [43] analyzed a firm's optimal time-to-market by considering its postlaunch production, pricing, and sales channel decisions. More recently, [23] considered all three dimensions of the tradeoff: time-to-market versus product performance versus product reliability.

Other studies investigated the interrelationship between the time-to-market and product quality for multiple product generations [9], [39]. For example, [57] examined the reuse/redesign, quality, time-to-market, and marketing decisions for two consecutive generations of a modular product. They fully characterized the firm's optimal strategies by providing conditions under which it should launch low- or high-innovation product with a short or long development time. In addition, they also considered in their model government regulations in terms of imposing reliability standards to assess the impact of such regulations on the three dimensions of the tradeoff. In this model, the overall product quality is improved by improving the quality of individual modules, and modules get improved by incurring a design cost that is convex increasing in the level of quality. They showed that a new product launch time postponement and an R&D budget increase can lead to product quality improvement, but better improvement in product quality can be achieved from launch time postponement (budget increase) when product design teams have low (high) PD productivity.

However, this literature did not investigate the impact of the product properties and the supply chain configuration on the product performance and development time tradeoff. Furthermore, there is scant research simultaneously examining the impact of all these factors on PD process and combining them into a single mathematical model that can assist managers in their quest to optimize their processes.

To fill this research gap, the article digs deeply into the product and process aspects that impact the product performance and the development time. Namely, we investigate the product architecture, complexity, newness, and the level of supplier involvement and discuss the direct relationship between these factors and the product performance and the PD time. We explore how each of these factors impacts the development time and in what way it influences the product performance.

Based on this discussion, we introduce a mathematical optimization model that captures the tradeoff between minimizing the PD time, on one hand, and improving the product performance on the other hand, for different PD scenarios. These different scenarios reflect different levels of factors pertaining to any PD process, in particular product complexity (related to the number of elements and functions designed in the product), newness (fraction of product parts to be redesigned in a new product) and level of supplier involvement (the amount of parts design outsourced to external suppliers). The objective of our model is to maximize the firm's revenue with respect to a time-limited market window.

Our model is based on a multistage process that originates with a system design phase followed by a detailed design phase and a phase of testing and integration before introducing the product into the marketplace. At the end of the testing stage a decision to go to market, not to go to market or iterate is made. If the decision is to rework, the detailed design stage is revisited before proceeding again to testing and integration. The model posits that corporations reap the revenues of their product in a finite marketing window, after which the product becomes obsolete and loses its value. This assumption mainly applies to highly competitive markets and technological products such as computers, tablets, smart phones in addition to software industry and automotive industry that also exhibit these demand characteristics. The mathematical model also applies to new products introducing modifications to an older model of the same product range rather than a "new to firm" or "new to the world product."

The article mainly focuses on the following questions.

1) Explore or evaluate the impact of product properties and the supply chain configuration on the product performance versus time-to-market tradeoff.
2) How do factors inherent to new PD process impact the managerial decisions within a firm aiming to maximize product revenue?
3) How should the effort be juggled between the system design phase and detailed design phase when factors pertaining to PD and supply chain decisions change?
4) Can managers apply the model to draw conclusions in real PD contexts?

After solving and analyzing the mathematical model, several managerial insights emerge. First, we found that when a simple product is under development it is advantageous to spend more time on the detailed design rather than the system design to improve the product quality, regardless of the supplier contribution or novelty level of the product. A shift to a more complex product should be coupled with an increased investment in the system design time, especially when the supplier involvement is low and the newness level is high. We also found out that compared to products characterized by a low level of newness, the development of novel products shall be accompanied with a slight increase in system design time, except when complex products are developed without relying on external suppliers. Under this scenario, a more important shift will be made in system design time. Finally, the development time of innovative and complex products is highly impacted by a dramatic change in supplier involvement. The increase in supplier involvement should be coupled with a reduction in system design and detailed design time for an optimized revenue generation.

This article also has implications for PD practitioners. A case study applying the empirical data of [11] and [12], [20], and [42] that gathered information on product newness, complexity and extent of supplier involvement within the automotive industry across several markets, suggests that the mathematical model can help managers forecast the optimal shift in time across the different PD stages when the factors of the product or process evolve throughout the subsequent models or generations.

II. Background

The PD process is the sequence of all the essential tasks that a firm must perform to develop, manufacture and sell a product [54]. These tasks include concept development (where customer needs are identified and product attributes are specified), system design (where product architecture is defined along with subsystems and interfaces identification), detailed design (where details of all product modules and components, such as geometry and material are specified), prototyping (where product validation and testing are performed), manufacturing (manufacturing design and planning for ramp-up and full production), and a whole chain of suppliers. Additionally, the PD process is a creative process operating in uncertain environments, which inevitably results in design iteration prevailing in the development of complex systems [36]. Design iteration (or simply iteration) is a feedback loop followed to revisit the work previously performed with a goal of improvement. Iterations help solve design problems, make ideas converge into real products and fix the incompatibilities between the components [35], [58].

A. Product Architecture

An essential aspect of a new product is its architecture. The product architecture is "the scheme by which the function of a product is allocated to physical components" [54]. The product architecture is the main structural scheme of the product, comprising information on the number of components forming the product and the relationship between the components [22].

The product architecture can be described using a continuum that spans the two extremes between a modular architecture and an integral one. A modular product architecture is known for its one to one mapping of functions to physical components and for the decoupled interfaces between the components [54]. The decoupling means that the interfaces are well specified so that a change in one component does not require a modification in other components. In the modular architecture, each functional element is implemented by one physical group (i.e., module) and the interfaces and interactions between the different physical groups are clear and well delineated [54]. In the integral product on the other hand, the functions are implemented by several physical modules, and unlike modular products, integral products do not show clear interfaces between the different physical groups [54]. Finally, the product architecture, which is defined during the system design phase of the PD process, is often associated with the complexity of a product. Designers tend to adopt the modular architecture when designing a complex product in order to simplify their design jobs [59]. Modularity is found to be an efficient way to manage the development of complex products [55]. The choice of the product architecture influences the product and the PD process in various ways; however, in this article we are interested in the impact of modularity on two major aspects: the product performance and the PD process management.

1) Correlation Between Product Architecture and Product Performance: Holtta *et al.* [26] distinguish between two types of performance: the business performance and the technical performance. The authors argue that technical constraints, such as lightweight, speed, and efficiency limit the advantage of modular products and favor the use of integral architecture. However, modular architectures emerge when a business driven project is developed [27] since they favor business performance through promoting mix and match [37], reconfigurability [5], upgrade, add-ons, adaptation [52] and more frequent product introduction into the market [55].

Later, Danese and Filippini [18] studied the mediating effect of the supplier involvement on the product modularity-performance relationship by examining 201 development projects from manufacturing plants in the mechanical, electronics, and transportation industries. Their analysis showed a significant positive impact of product modularity on product performance mediated by the degree of supplier involvement. The results of their study suggest that a PD firm can improve its performance by following a product modularity strategy, which paves the way for PD supplier collaboration and integration and leads to higher product and time performance.

2) Correlation Between Product Architecture and PD Process Cycle Time: According to Ulrich [52], more efforts are invested in system design phase when a modular product is being developed. This can be attributed to the time and effort spent to map functions to the different physical elements and to clearly and accurately define the interfaces between the modules and specify the relevant standards and protocols. Additionally, the detailed design of each component can be performed independently and in parallel for modular products [52]. The communication between the developing teams are infrequent. Whereas for the integral product, the component designers create a core team, within which many channels of communications are formed [52]. Finally, testing a modular product results in checking unanticipated interactions between the physical components of the product. This is usually considered a simple checking activity which results in fixing some bugs by modifying only few components [52]. More time is expected to be spent on testing and refinement integral products, since any error detected in this phase requires alteration to many components of the product [52].

B. Product Complexity

There is no consensus on the definition of a system complexity. Griffin [25] attributes the product complexity to the number of functions incorporated within a product. Similarly, in the engineering design literature, Ullman [53] defines complexity based on the number of functions and sub-functions that exist at the different product layers. On the other hand, Ethiraj and Levinthal [21] describe a complex system as a system composed of a "large number of parts that interact in a non-simple manner" and make the performance unpredicted. Vickery *et al.* [55] define the complexity as the number of components establishing a system. While, Novak and Eppinger [42], state that three main criteria contribute to a complex product: the number of components in a product that need to be designed and executed; the extent of interaction between the components; and the level of product novelty.

C. Outsourcing and Product Quality Improvement

Literature provides evidence that the supplier involvement in PD contributes to more innovative products and improves the development time [46]. The supplier involvement in PD can take place at the different stages of the process. In the early phase of concept generation, suppliers can provide valuable information on technology trends and contribute to value of engineering and more creative and innovative concepts [18]. During the detailed engineering phase, suppliers help identify risks, prevent potential problems and employ their expertise to design/produce innovative components or modules [18]. In the testing and integration phase, suppliers can perform additional tests that help identify potential future failures [18]. Overall, an increased supplier involvement contributes to an improved product quality, better features, enhanced characteristics, and less costly design [44].

D. Demand and Utility Function of New Products

In a competitive market, the demand of a given product is function of its value and the value of its rivals with respect to the customer. The logit model is frequently used to forecast the demand of a certain product, given the utility of this product and the total utilities of the competitors. The logit function is given by $D_i = D_T \frac{e^{U_i}}{\sum_{j=1}^{n} e^{U_j}}$ where U_i is the utility of the product, D_i is the demand, U_j is the utility of the competitor and n is the total number of competitors [14]. The logit model is built on the assumption that the customer's utility is the summation of two components, a deterministic component and a random component [13]. The probability that a chosen costumer buys form the firm is equal to the probability that this same firm's product produces higher utility than the competitors.

Knowing that the deterministic part is a function of product performance, Cohen *et al.* [13] introduced the product quality into the utility function such that the demand takes the following form: $D_i = D_T \frac{e^{\mathrm{U}(\mathrm{Q}_i)}}{e^{\mathrm{U}(\mathrm{Q}_i)} + e^{\mathrm{U}(\mathrm{Q}_C)}}$, where Q_i and Q_C are the firm's product quality and that of the competitor, respectively.

III. Model Formulation

In our proposed mathematical formulation, the traditional stage gate model is followed with ideas adopted from the agile model [15], [16]. We consider that three major consecutive stages contribute to the PD time frame. These three stages are the system design, detailed design and testing and integration [54]. The structure of the model, including the consecutive three stages of the PD, the marketing stage and the time allocated for each stage is represented in Fig. 1. At the end of the testing stage a decision to go to market, not to go to market or to iterate; i.e., rework is made. If the decision is to rework, the detailed design stage is revisited before proceeding again to testing and integration. Although it is possible to have iteration between system design and detailed design, it is less likely for that to happen in established product lines. This iterative loop (between phases 1 and 2) is akin of going back to the drawing board and redefining the product subsystems and modules. In our model, we assume that this will not happen. On the other hand, iteration between the design stage and testing stage is the predominant mode of feedback iteration in PD.

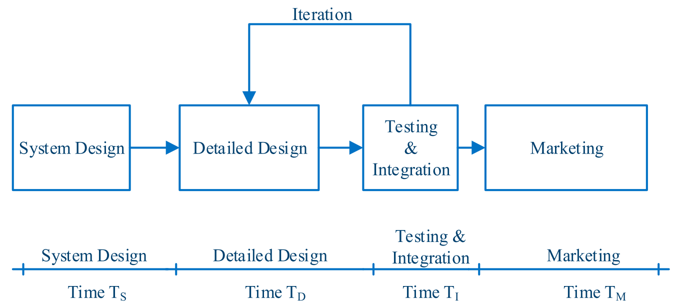

Fig. 1. Product development process model and time span.

As previously discussed, the time reduction of the PD process, contributes to a longer marketing window, the window of opportunity; however it is associated with low product quality, and therefore, a lower expected profit due to a reduced market share and/or lower product price [13]. On the other hand, an extended PD process results in higher product performance at the expense of a dwindling marketing window. Therefore, there is a tradeoff between the time spent on the system design, detailed design, testing and integration, i.e., the time to market on one hand and the quality/performance of the product on the other hand. The formulated mathematical model will capture this tradeoff, considering the product characteristics that affect the duration of each stage of the PD process and the level of product performance. Cohen *et al.* [13] our model is based on a multistage process spanning over a limited time frame, after which the product becomes obsolete, loses its value and its demand becomes insignificant. This assumption mainly applies to highly competitive markets and technological products, such as computers, tablets, smart phones in addition to software industry and automotive industry that also exhibit these demand characteristics. The model also applies to new products introducing modifications to an older model of the same product rather than a "new to firm" or "new to the world product".

III. System Design Phase

In the system design phase of the PD process, the system architects define the product architecture, identify the subsystems forming the product, specify the interfaces between the subsystems and establish the mapping of the physical components to the functional elements [51]; therefore, the product architecture emerges and the extent of product modularity is uncovered during this phase. The modularity of a product is defined through the process of "modularization" during which the degree of dependence and interaction between the different elements of the product is defined [5]. As a result of this process, the different elements are clustered within relatively independent modules such that the interaction between the elements within the module is maximized and the interaction across the modules is minimized [31]. Through the "systematic repetition of this process" the unnecessary interdependencies across the different clusters can be eliminated and the main modules emerge [5]. Therefore, a highly modular architecture is the result of deliberate effort and considerable time spent by the system engineers to identify the highly interactive cluster of elements.

It is understood that for a complex product—characterized by a large number of elements and a diverse number of functions assigned to the product—the process of modularization requires more effort and is more time consuming [7]. Clark and Fujimoto [11] agreed that the level of product complexity impacts the product planning phase currently known as the system design time. Compared to a simple system, a complex system requires more time spent by the system architect to identify the cluster of highly interactive element and group them into different modules. For instance, compared to automobiles, toaster ovens which are considered less complex, require less time spent on the system design phase to reach the same level of modularity [55].

Based on the above, our model reflects two major characteristics. First, a longer time spent by the system architect on the modularization process is associated with a higher level of product modularity [2], [56]. Second, a higher level of product complexity requires a longer time consumed by the system architects on the modularization process to reach a preset level of modularity. Therefore the modularity $m\ (T_s, \lambda)$ can be expressed in (1), where the system design time is designated by $T_s\ (0 \leq T_s \leq 1)$, and the product complexity by $\lambda\ (\lambda \geq 0)$

$$m\ = T_S^{\lambda}. \qquad (1)$$

B. Detail Design Phase

During the detailed design phase of the PD process, the design of different subsystems (as defined in the system design phase) is assigned to different teams working concurrently on the different subsystems. These activities can be performed in-house or outsourced. Each team, in-house team or supplier, defines the subsystem geometry, material, tolerances and other specifications during this stage of the process. The teams first spend an amount of time T_D to deliver the detailed design at a certain quality level Q at the end of this phase. This detailed design time T_D is considered the maximum time consumed by any of the different design teams working on the different subsystems. It is worth noting that the performance of the new product is positively related to the time spent on the PD process [8], [13], [25], [52].

In addition to the amount of time spent on the detailed design phase, the final quality of the product is also directly affected by its architecture defined during the system design phase [51]. In our model, a higher level of modularity is assumed to positively impact the level of product performance. This hypothesis was validated by [18] that confirmed the significant positive impact of product modularity on product performance mediated by the degree of supplier involvement.

Furthermore, the supplier involvement in PD is closely related to the level of product performance. Researchers agree that the product performance improves with an increased level of supplier involvement [44]. A supplier helps the firm achieve product distinctiveness, innovativeness and improve the development time [18].

Finally, the degree of product newness influences the time spent on the detail design to reach the desired level of performance. The product newness is defined by how much of the new product must be redesigned, compared to the product issued from the previous generation [25]. It reflects the familiarity of the firm with the design task and therefore the capability of the firm. Higher degrees of newness are found to extend the PD time [19], [29], [30]; if the engineers are more familiar with the product, a quicker time is expected to develop the product [25]. Therefore, we can assume that as the level of newness—from a firm perspective—increases, more time is required to reach the targeted product performance level.

Building upon the above discussion and literature, we assume a simple function for generating performance that reflects the following assumptions. First, the product performance improvement can be represented as a continuum $Q(T_D)$ such that a longer time spent on the detailed design phase is associated with a higher product performance. Second, integral products require more time, compared to modular products, spent by the design team to reach a preset performance level. Third, a higher degree of supplier involvement contributes to higher performance level. Finally, a higher level of product newness delays the achievement of the product performance target during the detailed design phase.

Therefore the product performance $Q\ (T_D, m, \mu,\ \alpha)$ can be expressed in (2), where T_D is the time is spent on detailed design $(0 \leq T_D \leq 1),\ m$ the level of product modularity defined in the system design phase $(0 \leq m \leq 1)$, μ the product newness $(0 \leq \mu \leq 1)$ and α the degree of supplier involvement $(0 \leq \alpha \leq 1)$

$$Q\ =\ T_D e^{-\frac{\mu}{\alpha+m}}. \qquad (2)$$

C. Testing and Integration

During the testing and integration stage of the PD process, the various subsystems designed by different design teams are tested to check their compatibility when brought together to function as one system. There is a probability that the product fails the testing and integration, in this case the detailed design is revisited to fix errors. In our model we assume that the additional amount of time spent on detailed design (during iteration) does not contribute to any improvement in product quality; however, this time is spent to fix the bugs, errors and incompatibilities to allow the product to be launched into the market. Therefore, we consider that the product quality is only determined by the original amount of time spent on the detailed design phase (T_D).

The failure of the design at this stage is correlated with its architecture previously defined in the system design phase. As the modularity of the product increases, the concurrently designed and clearly defined subsystems will be more likely to fit together to form a functioning product, unlike the integral product that will need further modifications and adjustments

Therefore, a higher level of modularity is associated with a lower probability of failure in testing and integration and a reduced number of iterations [35], [58].

Furthermore, the duration of the testing and integration phase is also closely related to the extent of supplier involvement. If the detailed design of a large fraction of components, or chunks of components, is outsourced to an external supplier, the outsourced parts will be less likely to fit together to form a functioning product from the first trial. Additional effort and collaboration between the firm and the suppliers will be required to further adjust and modify the parts in order to produce a functioning product. On the other hand, if the detail design is performed in house, a lower probability of failure in testing and integration is expected along with a reduced number of iterations.

Therefore, we assume that the time spent on testing and integration phase is given in (3), where "α" is the fraction of supplier involvement $(0 \leq \alpha \leq 1)$ and "*m*" is the level of product modularity $(0 \leq m \leq 1)$

$$T_{\text{INT}} = \alpha \ (1 - m) \, T_{D.} \tag{3}$$

C. D. Marketing

The revenues are only realized during the "market window" of the process. The demand function adopted in our model is the logit model. Cohen *et al.* [13] and Bayus [8], a log utility function is used for performance. $U_i = U(\text{Q}_i) = \ln(Q_i)$. Therefore, the demand rate ($D_i = D_T \frac{e^{U_i}}{\sum_{j=1}^{n} e^{U_j}}$) takes the form given in (4), where Q is the product performance level, Q_C is the competitive products performance level and *M* is the product category demand rate

$$D' \ (Q) = M \frac{Q}{Q + Q_C}. \tag{4}$$

Similar to [8] our model does not consider the advertising expenses and the advantageous return of other expenditures across competitors. However, unlike [8] that assumes sales to increase following the product lunch and reach a peak after a certain period then decline at the end of the marketing period, we consider that the market demand and sales rate are constant throughout the marketing phase. We consider also that the price is an exogenous factor that the firm cannot control as the firm is a price taker and not a price setter due to the high level of competition.

By placing the (1) through (4) of the mathematical formulation together, the revenue is calculated as in (5). The marketing window T_M is the total time spent on the whole project minus the duration consumed by the system design, detailed design and iterations. Therefore $T_M = T_T - T_S - T_D - T_{INT} = T_T - T_S - T_D - \alpha\,(1-m)T_D$

$$R \ (D', \, p, \, T_M) = D' \, . \, T_M.p \tag{5}$$

E. Complete Formulation

The model can be now written as an optimization problem expressed in (6). The target is to maximize the firm revenue, and solve for the main decision variables; i.e., the duration spent on each stage of the development process: the system design stage (or modularity) and the detailed design stage. Note that in our model we normalized to 1 the total duration of the PD process and the market window

$$\begin{aligned} \textbf{Max}\, R &= M. \frac{Q}{Q+Q_c} \left[T_T - T_S - T_D - \alpha \ (1-m) \, T_D \right] p \\ &= M. \frac{Q}{Q+Q_c} \left[1 - T_S - T_D - \alpha \ (1-m) \, T_D \right] p \\ &= M.\, p. \frac{T_D e^{-\frac{\mu}{\alpha+m}}}{T_D e^{-\frac{\mu}{\alpha+m}} + Q_c} \left[1 - m^{\frac{1}{\lambda}} - T_D - \alpha \ (1-m) \, T_D \right]. \end{aligned} \tag{6}$$

Subject to:

$$\text{Time limitation constraint}: \quad T_T - T_S - T_D - \alpha \ (1-m) \, T_D - T_M = 0 \tag{7}$$

$$\text{System design time}: \quad 0 \leq T_S \leq 1 \tag{8}$$

$$\text{Detailed design time}: \quad 0 \leq T_D \leq 1. \tag{9}$$

IV. Model Solution and Analysis

The objective of this analysis is to develop managerial insights to help PD managers in optimal time allocation, for different PD phases, that maximizes the revenue depending on the characteristics of the product. Since we are after insights, it is not useful to present the optimal solution for generic values of the various parameters. Instead, we opted for presenting the optimal solution for specific scenarios that simulate real PD environments. In order to build these scenarios, the different values for the input parameters need to be carefully assessed. The main model parameters and their respective numerical ranges are given in Table I.

Q_c and *Q*, defined in (2), have the same unit and fall within the same range of values. The lower limit of *Q* is 0, reflecting a very poor quality of the product. Whereas the upper limit is calculated when T_D tends to 1, μ (newness) tends to 0, and α (supplier involvement) and *m* (modularity) tend to 1. Therefore, the upper limit is calculated using (2) to be 1.

Even though the values of Q_c range between 0 and 1, the PD process represented by our model takes place in a competitive environment; therefore, our model is evaluated only for the upper range of Q_c, between 0.5 and 1. The ranges given in Table I cover most PD processes.

Each PD scenario is characterized by a specific level of product newness μ, degree of complexity λ, supplier involvement α, competition level Q_c, level of product market share *M* and product price *p*. It is worth noting that a multiplicative constant does not impact the optimal solution, therefore, the market share *M* and the product price *p* do not affect the optimal solution in terms of time allocation between system design time T_S and detailed design T_D; however, their values impact the calculation of the firm's revenue. As our objective is not to calculate the

TABLE I
LIST OF PARAMETERS USED IN THE PROPOSED MODEL AND THE RESPECTIVE NUMERICAL RANGES

Parameter	Definition	Range	Reference
m	Modularity	0-1	Holtta-Otto & de Weck (2007) Mikkola (2006)
λ	Complexity	0-1	Samy and El Maraghy (2012) Novak and Eppinger (2001)
μ	Newness	0-1	Griffin (1997) Clark & Fujimoto (1989)
α	Supplier involvement	0-1	Clark & Fujimoto (1989) Danese & Filippini (2010)
Q_c	Competitor's product quality	0-1	Calculated

TABLE II
SIMULATION RESULTS FOR $Q_c = 1$

PD Scenario	1	2	3	4	5	6	7	8
Competitor's quality (Q_c)	1	1	1	1	1	1	1	1
Complexity (λ)	0.1	0.1	0.9	0.9	0.1	0.1	0.9	0.9
Supplier involvement (α)	0.1	0.1	0.1	0.1	0.9	0.9	0.9	0.9
Newness (μ)	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.9
Optimal detailed design (T_D^*)	0.406	0.433	0.372	0.283	0.329	0.349	0.238	0.250
Optimal modularity (m^*)	0.614	0.734	0.120	0.424	0.681	0.711	0.000	0.048
Optimal system design (T_S^*)	0.008	0.045	0.094	0.386	0.021	0.033	0.000	0.028
Integration time (T_I)	0.016	0.012	0.033	0.016	0.095	0.091	0.214	0.214
Marketing window (T_M)	0.571	0.510	0.501	0.315	0.555	0.527	0.548	0.508

revenue, but to find the optimal allocation of time for managerial conclusions, M and p are dropped from further consideration in the analysis.

The PD scenarios (1 through 8) given in Table II are characterized by the same competition level Q_c but different degrees of newness μ, supplier involvement α, and complexity λ. Two numerical values for each of the parameters are considered to simulate its low and high level. These values are 0.1 and 0.9. Therefore, the eight sets of numerical values reflect the eight possible combinations of newness, complexity, and degree of supplier involvement.

The PD project represented by the first scenario is characterized by a low level of complexity ($\lambda = 0.1$), low level of supplier involvement ($\alpha = 0.1$) and low newness ($\mu = 0.1$). Whereas the second scenario reflects a PD characterized by a low level of complexity ($\lambda = 0.1$), low level of supplier involvement ($\alpha = 0.1$) and a high level of newness ($\mu = 0.9$).

For each given scenario, the optimal solution is obtained using Maple software, which solves for the optimal $T_D{}^*$ and modularity m^*, then the values of $T_S{}^*$ T_{int} are recalculated based on (1) and (3). It can be readily shown that the optimal solution generated by Maple for each scenario and represented by a point S (m^*, $T_D{}^*$) is a strong local maximum. The proof entails evaluating the gradient of the objective function and the determinants of the first and second order leading principals of the Hessian matrix at each point S (m^*, $T_D{}^*$) for each PD scenarios [28].

The same calculations were also repeated for the lower range of competition (i.e., for $Q_c = 0.5$). The results show that minimal differences in $T_D{}^*$ and $T_S{}^*$ are detected between the two cases ($Q_c = 1$ versus $Q_c = 0.5$). These differences are less than 10%, showing relatively low sensitivity of the model to competitors' quality. Therefore, the analysis that follows is applicable for average and high levels of competition.

A. Sensitivity Analysis

In this section, we assess the impact of each input parameter on the optimal solution of the proposed model. The main objective here is to draw some generic conclusions and insights regarding the management of the process based on estimates of the different parameters.

1) Impact of Complexity: Fig. 2 shows the optimal allocation of time between system design and detailed design for the low complexity level scenarios (i.e., scenarios 1, 2, 5 and 6 in Table II). The optimal solutions of all cases fall within the

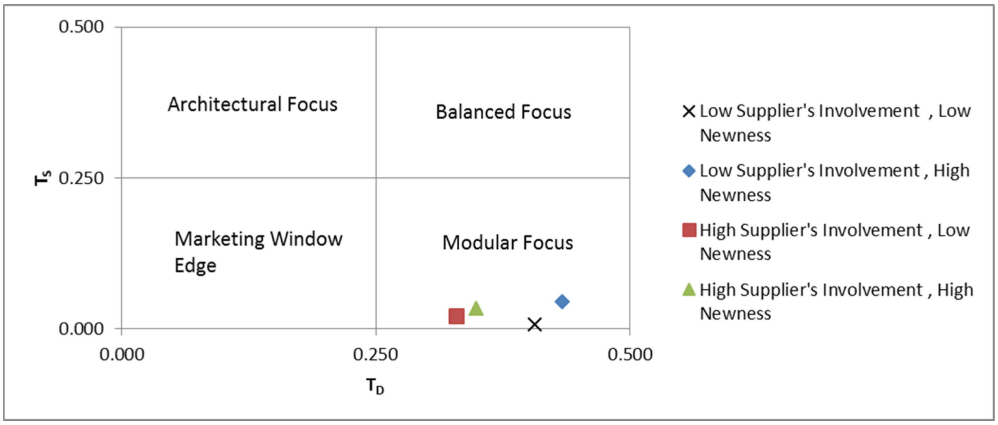

Fig. 2. Optimal solutions for low complexity scenarios.

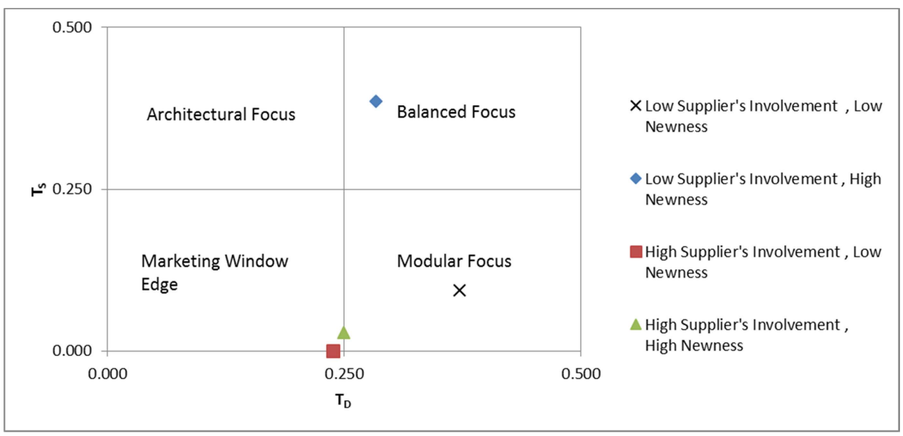

Fig. 3. Optimal solutions for high complexity scenarios.

quadrant characterized by a high amount of time and effort spent on detailed design rather than the system design. This quadrant is referred to as the "modular focus" quadrant. The plot indicates that when the level of product complexity is low, it is optimal to spend more time on detailed design and very little time on system design. This low complexity level is coupled with an implicitly high level of modularity achieved through minor effort put into the modularization process. The high modularity leads to high performance along with long time spent on detailed design which optimizes the revenues.

The impact of an increase in product complexity is shown in the Fig. 3. For the two cases characterized by high level of supplier involvement, the optimal solution is shifted to the left with minor modification in T_S. This is attributed to the fact that a high level of supplier involvement coupled with a low level of modularity (resulting from an increased complexity) require a long testing and integration effort, irrespective of the newness level. Therefore, in this case, it is optimal to maximize the marketing window by spending less time on detailed design in order to balance the extra time needed for testing and integration. It is more advantageous to put less effort into modularization to save system design time rather than benefiting from the positive impact of a higher modularity on performance.

However, for a low level of supplier involvement, associated with a low level of newness, a radical increase in the product complexity contributes to a slight increase in the "modularization" time with minor change in the detail design time. In this scenario, the testing and integration time is minimum, due to low supplier involvement. The higher resulting modularity coupled with the low level of newness improve the performance level and therefore optimizes the revenues.

Finally, the impact of a drastic increase in product complexity on a low level of supplier involvement and high newness scenario leads to a higher system design time and lower detailed design time; the solution is shifted to the "balanced focus" zone. The high level of newness added to the low supplier involvement will make it hard for the company to improve performance; this could only be compensated by an increase in modularity level. This extra time spent on modularization should also be traded off with a slightly less time spent on detailed design to maintain a reasonable marketing window and allow the company to sell the product and generate revenue.

2) Impact of Newness: Similar analysis is carried out to investigate the impact of a change in product newness on the optimal solution (i.e., the time allocation to the different phases on the PD process). For the low level of newness (see Fig. 4),

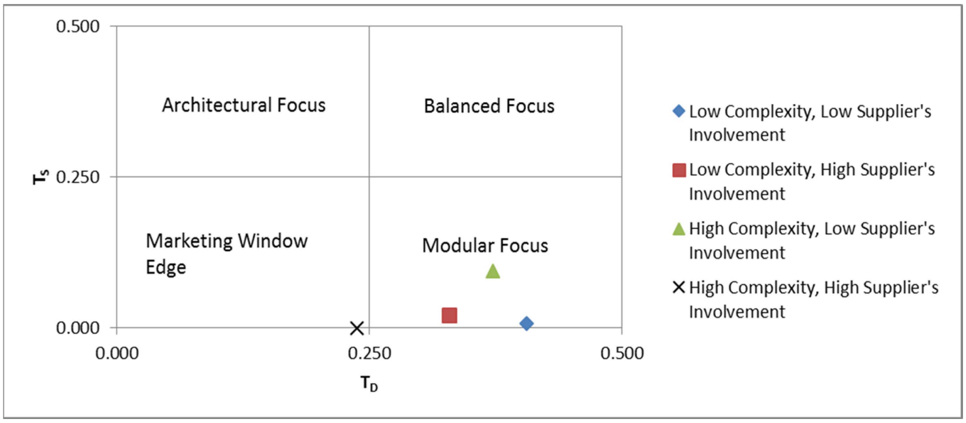

Fig. 4. Optimal solutions for low newness scenarios.

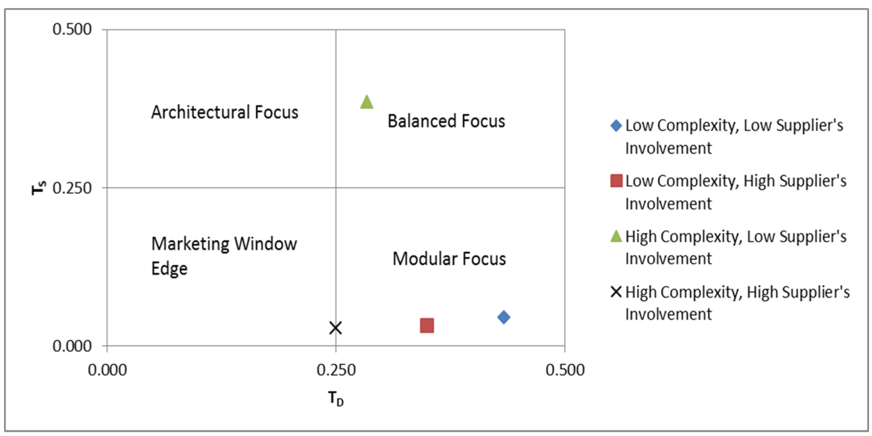

Fig. 5. Optimal solutions for high newness scenarios.

most scenarios fall within the modular focus zone, where the time spent on the detailed design of each module considerably exceeds the time spent on system design. Except for the scenario where both complexity and supplier involvement are high, where the solution falls within the “marketing edge” zone, and both T_D and T_S are relatively low. This case is associated with high testing and integration time (low modularity and high supplier involvement) and in order to gain marketing window time some T_D duration must be saved.

In case of an increase in newness level (see Fig. 5), the low complexity scenarios remain in the “modular focus” zone, with little time spent on system design. The scenario of high complexity and high supplier involvement was subject to a slight shift to the right towards a higher modular focus. This is due to the negative impact of the newness on the product performance, an increase in T_D tries to recuperate some lost performance level due to the change in newness levels.

The optimal solution of the “high complexity, low supplier involvement” case is shifted from the “modular focus” zone to the “balanced focus” zone following an increase in the newness level. The detailed design time is reduced, and the system design time is increased. The system design time is increased to improve the modularity, and therefore, the product performance and to balance the negative impact of high newness, low supplier involvement and the implicitly low modularity on the product quality. T_D is slightly reduced to maintain an optimum marketing window.

3) Impact of Supplier Involvement: Fig. 6 shows the solution of low complexity scenarios that fall within the “modular focus” category where the company is supposed to spend a higher amount of time on the detailed design phase compared to the system design. When a high complexity is coupled with low newness and supplier involvement, a slightly higher T_S is required to increase the modularity and therefore enhance the product performance. The integration time, T_I, in this case is very low since the supplier involvement is minor.

The fourth scenario characterized by a high complexity, high newness and low supplier involvement, all contributing to a low performance, the only way to contribute to some performance is to spend more time on system design and increase the modularity in order to improve the product performance. That’s why the solution falls in the “balanced focus” zone.

The drastic change in supplier involvement, shown in Fig. 7, only impacts the high complexity scenarios by reducing the time spent on T_D and T_S. For low newness, high complexity (low modularity), the increase in supplier involvement leads

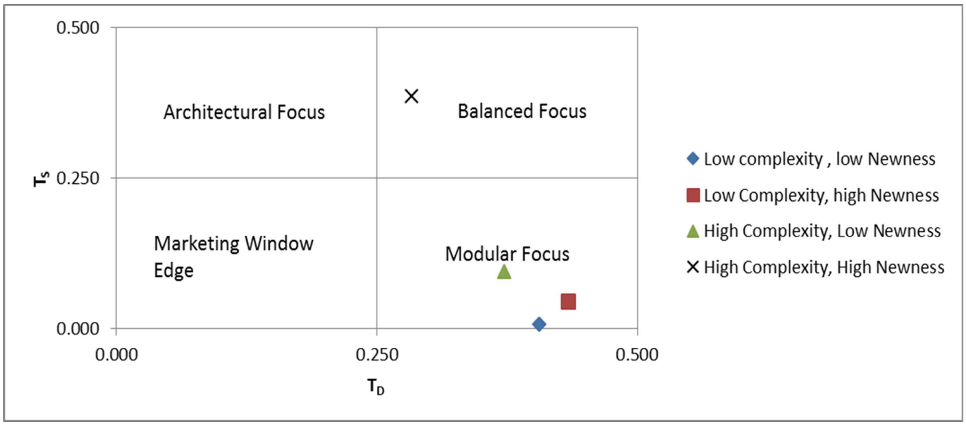

Fig. 6. Optimal solutions for low supplier involvement scenarios.

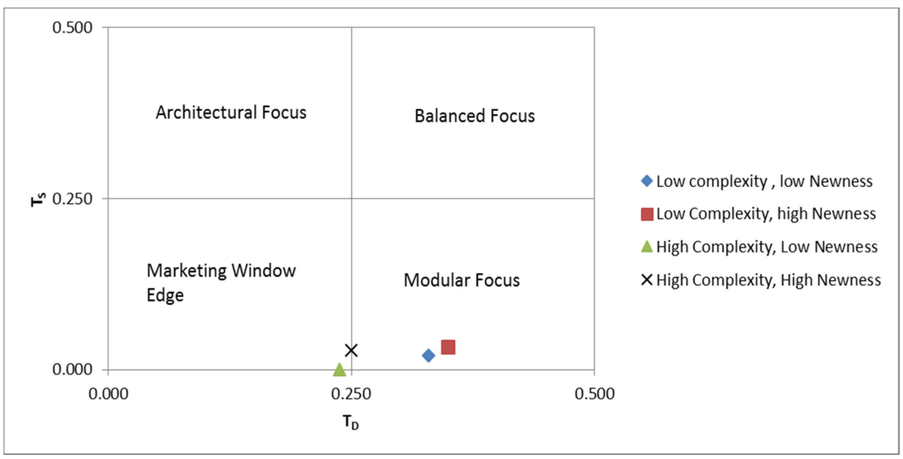

Fig. 7. Optimal solutions for high supplier involvement scenarios.

to an increase in testing and integration time (T_I), therefore, the marketing window is optimized by reducing the time spent on both the detailed design and system design. Some level of product performance is maintained due to the low newness levels and high supplier involvement.

Similarly, for high complexity (low modularity) and high newness (deteriorating the performance level) a high supplier involvement increases the testing and integration time, therefore the system design time should be reduced to gain some marketing window edge. The detailed design T_D cannot be compromised since that will affect the product performance level. Therefore, when developing a complex and innovative product, a firm is advised to involve more external suppliers to design, develop a higher fraction of its parts. This will help the firm optimize the marketing window, maximize the product performance and generate high revenues.

V. Case Study

This case study is based on data pertaining to the automotive industry in three major markets: the Japanese market; the European market; and the US market. The data is obtained from [11], [12], [20], and [42]. It is worth noting that the PD process of the automobile industry did not radically change since the 1990s [24].

The automotive industry was subject to several changes between the years 1980s and 1990s. The extent of supplier involvement in cars development was not constant over the course of the years and across the different markets; the Japanese and US producers expanded the share of suppliers involvement between the 1980s and 1990s whereas the European producers limited the suppliers contribution during the same period ([11] and [12], [20]). Similarly, the degree of novelty in cars parts also varied between the 1980s and 1990s in different levels across the different markets. The level of automobile complexity has also increased given the technological, safety and material advancements.

The data in [11], [12], and [20] reflect the dynamics of the automobile development industry between 1980s and1990s. It comprises the essential factors inherent to car development (newness levels and extent of supplier involvement) in addition to the information related to PD time. This set of existing data is used to determine and calculate numerical values of the formulated model parameters (complexity, newness, and

TABLE III
DATA EXTRACTED FROM CLARK AND FUJIMOTO [11]

	Strategic- regional groups / variables	Japanese volume producer	U.S volume producer	European Volume producer
Lead time	Overall Lead time (months) (OLT)`	43.3	60.3	66.5
	Planning Lead time (months)	13.6	19.3	20.6
	Engineering Lead time (months)	32.2	39.7	45.9
	T_{total} (2* Overall lead time)	**86.6**	**120.6**	**133**
	Average price (1987 US dollars)	8,783	13,702	23,785
Project scope	off the shelf parts (OP)	18%	45%	29%
	newness (μ)	**82%**	**55%**	**71%**
	Supplier involvement (%)			
	Supplier proprietary (SP)	8%	3%	7%
	Black Box (BB)	62%	16%	39%
	Detail-controlled (DC)	30%	81%	54%
	Supplier-engineering ratio (α)	**51%**	**14%**	**34%**

supplier involvement). The calculated values are used to run the model and generate numerical output. This output is analyzed by comparing it to existing figures in terms of allocation of time across the different stages of the PD process.

A. Numerical Values for the Mathematical Model

Between 1985 and 1988, Fujimoto and Clark collected data from 24 car production projects in Europe, Japan and the United States [11], [12]. Among the rich dataset provided by Clark and Fujimoto, three parameters, detailed in the following sections and given in Table III, are shared with our proposed mathematical model, therefore their respective numerical values will be used in this mathematical application.

1) Newness (μ)

The value of newness is determined from the value of the "Off the shelf parts" (OP). The latter is defined as the fraction of components that is common to previous or other models. Newness, the fraction of newly designed parts, is therefore calculated by 1- "off the shelf part"

$$\mu = 1 - \mathrm{OP}. \tag{10}$$

2) Supplier Involvement (α)

The data collected by Clark and Fujimoto on the parts procured from suppliers are broken down into three different categories, distinguishing the levels of supplier engineering involvement; the supplier proprietary (SP) part, defined by the fraction of the elements or parts that are completely developed by suppliers, the black box (BB) part that comprises the parts whose basic design is carried out by the main car developer whereas their detailed design is performed by the supplier and finally the detail controlled (DC) part, which covers the elements that are completely developed by the car producer.

Further, a ratio called "the supplier engineering ratio" is calculated. It is defined as the fraction of the total engineering hours accounted by suppliers. This value is calculated assuming that 100% of engineering work is done by suppliers for proprietary parts (SP) and 70% of engineering work is done in BB parts and 0% in detail controlled. This supplier engineering ratio value is used to determine parameter "α" in our model

$$\alpha = \mathrm{SP} + 0.7 \times \mathrm{BB}. \tag{11}$$

3) Lead Time ($\mathrm{T_S}$ and $\mathrm{T_D}$)

As defined previously, the "lead time" refers to the duration spanning between the concept generation and the product introduction into the market; it includes four stages: concept generation; product planning; product engineering; and process engineering. Clark and Fujimoto [11] grouped the first two stages (concept generation and product planning) of the PD process under a wider category: the "planning phase" and the last two (product engineering and process engineering) under the "engineering phase".

4) Planning Versus Engineering

Planning activities lay the ground for engineering work by determining the structure and function of the new product [11]. The result of the planning phase is a decomposition of the product into well delineated cluster of components, each of which can be handled separately during the engineering phase [11]. On the other hand, the "engineering phase" follows the

TABLE IV
SUMMARY OF OPTIMAL SOLUTIONS FOR THE DIFFERENT CAR PRODUCERS (YEARS 1980S)

	Japanese volume producer	U.S volume producer	European Volume producer
$T_D{}^*$	0.322	0.375	0.346
m^*	0.373	0.429	0.397
$T_s{}^*$ ($T_S = m^{\frac{1}{\lambda}}$)	0.096	0.133	0.111
$T_I = (\alpha.(1\text{-}m).T_D)$	0.104	0.030	0.072
$T_D + T_I$	0.426	0.405	0.418
T_{total} (months)	86.6	120.6	133
$T_S{}^*$(months)	8	16.1	14.7
$T_D{}^*$ (months)	28	45	46
T_I(months)	9	3.7	9.5
T_D+T_I(months)	37	48.8	55.6

decomposition of the product into smaller parts in the planning phase, the problem solving for each component (or cluster of components) goes independently [11].

According to the above definitions provided by [12] we can conclude that the planning time is equivalent to the system design time in our model (T_S) and the engineering time is equivalent to the detailed engineering time added to the testing and integration ($T_D + T_I$) since the engineering phase incorporates testing and prototyping

$$T_S = \text{Planningtime} = \text{Concept Generation} + \text{Product Planning}$$

$$T_D + T_I = \text{Engineering time} = \text{Product Engineering} + \text{Process Engineering}.$$

5) *Complexity*

The value of complexity was adopted from [42] that aimed to study the effect of complexity level on the outsourcing decision. According to [42], the product complexity that is driven by a number of factors including the targeted level of performance, architecture and adopted technology, is defined by three main criteria: the number of elements within a product; the extent of interaction between the elements; and the level of product novelty. These three criteria are evaluated for the auto industry by collecting data through on-site interviews with CEOs, project engineers, and project managers. The complexity of each sub-system within the car is evaluated separately; that is, the complexity of the suspension, brakes, transmission, engine, steering, body, and electrical systems is evaluated on a scale of 0 to 1 and the mean complexity of the whole product is then calculated. The mean complexity of the cars is determined to be 0.42. This value will be used in our analysis and calculations.

B. Numerical Solution—Results: Table III gives the data provided by Clark and Fujimoto needed to solve the mathematical model for each of the Japanese, European, and American scenarios. The values in bold are calculated values, which are not originally present in the set of data provided in [11]. T_{total} which is by definition the concept to market lead time added to the market window, it is the time at which the car model becomes obsolete due to the introduction of a competing model by rivals or a newer model by the same car developer. According to Clark and Fujimoto, car developers forecast for a period that is at least twice the concept to market lead time. For instance, if the lead time is six years the company shall forecast 6–12 years ahead. Therefore, T_{total} is assumed to be twice the duration of the overall lead time (OLT)

$$T_{\text{total}} = 2 \times \text{OLT}. \quad (12)$$

Finally, the optimization problem is solved using Maple.

The optimal solutions generated by Maple for the three car producers are given in Table IV, in addition to the calculated values of testing and integration time T_I. The values for $T_S*$and T_D* are recalculated in units of months considering the T_{total} previously calculated. These values are compared with the empirical data collected by Clark and Fujimoto in Table V.

C. *Analysis and Discussion*

The data collected in the 1980s on the automotive industry are updated by [20]. This updated data is given in Table VI. The same optimization exercise is performed based on these updated values and assuming that the complexity of automobiles has also increased from 1980s through 1990s from 0.42 to 0.5 due to the incorporation of more advanced mechanical systems and the integration of electronic features to improve safety, fuel efficiency and advanced diagnostics. The calculated optimal solutions are given in Table VII. The values for $T_S*$and T_D* are recalculated in units of months in Table VII considering the T_{total} calculated previously. Finally, Table VIII gives a comparison between the calculated values and empirical values for the years 1990s.

As observed in Tables V and VIII, the output of the model and the empirical data are not exactly equal, however the values are comparable. In fact, the purpose of the model is not to get

TABLE V
COMPARISON BETWEEN CALCULATED AND EMPIRICAL VALUES (FOR YEARS 1980S)

	Japanese volume producer		American volume producer		European Volume producer	
	Calculated	Empirical	Calculated	Empirical	Calculated	Empirical
T_s (months)	8	13.6	16.1	19.3	14.7	20.6
T_D+T_I(months)	37	32.2	48.8	39.7	55.6	45.9
$T_{lead\ time}$	45	43.3	64.9	60.3	70.3	66.5

TABLE VI
AUTOMOTIVE INDUSTRY DATA FOR THE YEARS 1990S, EXTRACTED FROM [20]

	Strategic- regional groups / variables	Japanese volume producer	U.S volume producer	European Volume producer
Lead time	Overall Lead time (months)	51	52	59
	Planning Lead time (months)	19	17	22
	Engineering Lead time (months)	28	33	32
	T_{total} (2* Overall lead time)	102	104	118
Project scope	off the shelf parts	28%	32%	32%
	newness (μ)	72%	68%	68%
	Supplier involvement (% of parts cost)			
	Supplier proprietary (SP)	6%	12%	12%
	Black Box (BB)	55%	30%	24%
	Detail-controlled (DC)	39%	58%	64%
	Supplier-engineering ratio (α)	45%	33%	29%

TABLE VII
CALCULATED OPTIMAL LEAD TIMES FOR THE DIFFERENT CAR PRODUCERS (YEARS 1990S)

	Japanese volume producer	U.S volume producer	European Volume producer
T_D^*	0.323	0.339	0.344
m^*	0.325	0.354	0.369
T_S^* ($T_S = m^{\frac{1}{\lambda}}$)	0.105	0.126	0.136
$T_I = (\alpha.(1-m).T_D)$	0.097	0.072	0.063
T_D+T_{int}	0.419	0.411	0.407
T_{total} (months)	102	104	118
T_s^*(months)	11	13.1	16.0
T_D^* (months)	33	35.3	40.6
T_{int}(months)	10	7.5	7.4
T_D+T_{int} (months)	43	42.8	48.0

TABLE VIII
COMPARISON BETWEEN CALCULATED AND EMPIRICAL VALUES (FOR YEARS 1990S)

	Japanese volume producer		American volume producer		European Volume producer	
	Calculated	Empirical	Calculated	Empirical	Calculated	Empirical
T_s (months)	11	19	13.1	17	16.0	22
T_D+T_I(months)	43	28	42.8	33	48.0	32
$T_{lead\ time}$	54	51	55.9	52	64	59

an accurate solution for the exact time that a firm must allocate to each phase of the development process; on the contrary the model aims to generate general managerial insights that help companies find the best division of time between the different project phases; in addition, there is always a difference between the theoretical values that a model generates and the real values that industries end up spending due to unanticipated events they face during project execution. Furthermore, the introduced mathematical model is a general model that can be applied to all industries, it is not tailored for the automotive industry that has its own characteristics and particularities.

Comparing the information in Tables V and VIII, that summarize the output of the model and the empirical data for the years 1980s and 1990s, respectively, we can observe that the model succeeded to forecast the change in time allocation between planning and engineering for the American and European car producers. The model output anticipated a decrease in system design time from 16 to 13 months (3 months difference) whereas a decrease from 19 to 17 months was observed (2 months difference). In engineering time, the model also anticipated a decrease in time from 48 to 42.8 months (around 6 months difference) and in reality, the reduction in engineering time was from 39 to 33 months (6 months difference). This reduction in OLT may be attributed to the increase in supplier involvement from 14% to 33% which led the American producers to save time in planning and the overall engineering time.

For the European car developers, the model calculated approximately one month increase in the system design time, from 14.7 to 16 months. In reality, the planning time for the European developers has increased by one month from 20.6 to 22 months. Regarding the engineering time, the calculated reduction in this phase was 8 months from 56 to 48, and however, the observed reduction was by 14 months from 46 to 32 months. For a lower new parts ratio and a lower supplier engineering involvement along with the increase in the level of cars complexity, European car developers had to spend more time planning the product and grouping the highly interactive elements within modules and defining the interfaces between the subsystems. With these clearly defined subsystems the European car developers were able to spend less time in detail design and end up optimizing the marketing window. For the Japanese scenario on the other hand, the model did not anticipate the change in time allocation. What is particularly observed in the Japanese scenario is that, unlike European and American developers, where a reduction of the OLT is noticed, the Japanese model data show a more prolonged OLT in 1990s compared to 1980s. Therefore, we can hypothesize that the Japanese firms did not optimize their performance by applying the optimal time allocation to maximize revenues. Japanese firms might not have been the "best-practice" firms in optimizing the PD process and speeding their product launch into the market.

VI. CONCLUSION

In this article, a mathematical model was formulated and analyzed to examine the tradeoff between the time allocated for the different stages of the PD process and product performance considering different PD scenarios. These scenarios differ in three important factors that were part of any PD process. These factors were product complexity, product newness, and the level of supplier involvement. PD managers can refer to the simulation results to generate general guidelines regarding the development time and effort allocation across the different stages of their PD process based on their product characteristics and their outsourcing strategy. In the event of simple PD, managers should plan for a longer detailed design time (compared to a system design time) in order to improve the product quality. A shift to complex PD shall be coupled with an increased investment in the system design time especially when the supplier involvement was low and the product newness level is high. In case firms shift from products characterized by a low level of newness to develop innovative products, an increased system design time shall be accounted for when innovative and complex products were developed within a limited supplier involvement context. Firms shall also anticipate a reduction in both system design and detailed design time with an expanded external supplier scope in complex PD.

Developers can also run the model to observe the optimal shift and change in the time allocation for the different process stages should the characteristics of the product change based on the changing customers' needs. The presented case study suggested that it was practical to run this model by assigning numerical values to the various parameters in order to draw important managerial insights. The case study also showed that the output of the model was in line with the collected data for two out of three evaluated scenarios relating to the world autoindustry. By gathering data on the product complexity, newness and the extent of supplier involvement, firms can use the mathematical model to better forecast the time allocation across the different project stages and improve their prediction for the introduction time into the marketplace. This approach helps firms better manage their portfolio of PD and optimally schedule their stream of new products. This will also help firms maintain their competitive edge in the long term.

In future work, the model could be tailored to address the particularities of a potential industry. For instance, in certain industries, firms spend a considerable amount of time on the manufacturing stage (e.g., mechanical equipment development) while firms in a different industry compress or skip the same stage (e.g., software development). Other industries are characterized by a substantial focus on testing and prototyping (e.g., firms developing products in the environmental field and pharmaceutical industry). An enhanced model that meets a specific industry's particularities will help reduce the gap between the model optimal solution on one hand and the real allocation of time leading to an optimal revenue generation on the other hand.

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Ali Yassine received the B.E. degree in mechanical engineering from the American University of Beirut, Lebanon, in 1988 and the M.S. and Ph.D. degrees in industrial and manufacturing engineering from Wayne State University, Detroit, MI, USA, in 1989 and 1994, respectively.

He is currently a Professor of engineering management with the Department of Industrial Engineering and Management, the American University of Beirut. From 2001 to 2008, he was an Assistant Professor with the Department of Industrial and Systems Engineering, University of Illinois at Urbana-Champaign, Champaign, IL, USA. Prior to joining UIUC, he was a Research Scientist with MIT Center for Technology, Policy and Industrial Development. He is currently a Leading Researcher and an Educator in the areas of Engineering Design and Product Development. He is an Expert in using operations research and machine learning techniques (i.e., model-based and data-driven approaches) for managing the design and development of complex engineering products / systems. He has authored more than 100 articles, in leading engineering and management academic journals and refereed international conferences, covering product design and development, engineering and project management, systems and entrepreneurial engineering, and management of technology and technological innovations.

Sally Souweid received the B.E. degree in civil and environmental engineering and the master's degree in engineering management from the American University of Beirut, Beirut, Lebanon, in 2012 and 2019, respectively.

From 2016 to 2019, she was a Graduate Research Assistant with the Department of Industrial Engineering and Management, American University of Beirut. Her areas of research interests include product development, operations research and energy optimization.