Achieving New Product Development Excellence in an Uncertain Environment: An Empirical Study in the Electronics Manufacturing Sector from the Dynamic Capabilities Perspective

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A major challenge faced by managers in an uncertain environment is to make sound decisions on managerial interventions to retain the firm's competitiveness. The dynamic capability perspective explains how a firm can remain competitive in a changing or uncertain environment. This study investigates how a firm in the electronics manufacturing sector that has high levels of environmental dynamism can achieve excellence in new product development services and remain competitive. Drawing upon the dynamic capability literature, first, the dynamic capability of a firm is operationalized through sensing capability, learning capability, integrating capability, and coordinating capability. We benchmarked the dynamic capabilities of 30 new product development units in the electronics manufacturing sector against their performance employing data envelopment analysis in an empirical study. The benchmarking results indicate that a significant proportion of the firms are operating at efficiencies below that of the best-in-class, and it also classifies the causes into managerial inefficiencies and scale inefficiencies due to employment of ineffective or obsolete technologies and processes. The combination of dynamic capability concept and the data envelopment analysis for benchmarking gives a very powerful tool for managers to achieve new product development excellence in an uncertain environment.

Keywords: Dynamic Capabilities, Data Envelopment Analysis, New Product Development, Performance Measurement, Benchmarking, Multi-Criteria Decision Making

1. Introduction

The perpetual challenge faced by any firm is how to create and sustain a competitive advantage. Even if a firm exhibits superior performance at one point in time, to sustain the advantage is no easy task, especially if, the environment is changing drastically. The electronics industry all over the world exhibits high levels of technological and market dynamism and is an ideal setting to find an answer to the above problem.

Success of New Product Development (NPD) program of an organization depends on launching products that meet and exceed customer requirements at the right price, at the right time. In today's competitive environment, how well an organization achieves the above, when compared to its competitors determines its chances of success. The capability to do this in a sustained manner is decided by its dynamic capability. According to Teece et.al, (1997) dynamic capabilities are "the ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. In the context of this study dynamic capabilities are defined as the ability to reconfigure the existing capabilities to adapt to the changing environment.

Following the suggestions by Pavlou et al. (2011) this paper focuses on identifying the optimum level of dynamic capability in the context of NPD units of the electronics industry to achieve sustainable performance. The choice of the ESDM industry stems from the fact that it exhibits high levels of technological and market dynamism due to globalization. Theoretically, it builds on the previous research arguing that a firm needs to benchmark its dynamic capability with respect to competition and decide on suitable interventions to remain competitive in the long run especially in the changing or uncertain environment.

Empirically this paper investigates the efficiency and effectiveness of the dynamic capabilities of each NPD unit with respect to competition to maintain sustainable performance.

By investigating the impact of dynamic capability on NPD performance, the study makes at least three contributions to previous research. First and foremost, in the context of dynamic capability research, the DEA method is applied for the first time to benchmark the performance of NPD units in the ESDM sector. Even though Trappey et al., (2007) has employed DEA in the context of NPD, it is for developing a project planning and management decision support methodology for NPD that can optimally allocate resources and dynamically respond to unexpected delays and budget overruns. Second, the study provides a comprehensive method to policymakers and NPD managers for evaluating the performance of NPD units in terms of their relative efficiencies. The results can also be used for target setting in terms of their capabilities and to decide on other interventions for improved performance.

2. Literature Review

2.1 Dynamic Capability

The dynamic capability can be seen as a capability that will help an organization adapt its existing operational capabilities to sustain its competitive advantage in a rapidly changing customer and technology space in the long run.

Teece et al. (1997) define the term ‘dynamic’ as the capability to renew competences in order to achieve congruence with the changing environment. It has four dimensions. The first one *sensing capability* is the ability of the firm to sense its environment (Pavlou and Sawy, 2006; Menon and Mohanty, 2008) in order to detect opportunities or threats. The second one *learning capability* is the ability to acquire, learn, transform and exploit existing knowledge to generate new knowledge (Zahra and George, 2002, Menon and Mohanty, 2008). *Integrating capability* covers the ability to combine individual knowledge into the unit’s new operational capabilities. It facilitates re-configuration through three routines; contribution, representation, and interrelation that helps routinization of reconfigured operational capabilities (Okhuysen & Eisenhardt, 2002). The fourth dimension of DC is the *coordination capability*. According to Eisenhardt & Brown, (1999), coordinating capability helps NPD units assign the right person to the right task and better synchronize their tasks and activities (Helfat&Peteraf, 2003).

2.2 New Product Development

The study of the past NPD literature reports that the methodology used in NPD has not changed much since the last 30 years, Ernst (2002). Product development is the set of activities driven from the perception of a market opportunity and culminating in the production, sale, and delivery of a product. The ability of a firm to identify customer needs and quickly translate them into products that can be produced at low costs determines their success (Ulrich and Eppinger, 2004).According to Esper et al. (2007), organizations' survival is dependent on the competitive advantage of their new products. NPD has thus become a key differentiator and strategic activity through which many firms make an increasingly significant contribution to sales and profits (Koufteros et al. 2005)

In today’s world, the two major challenges faced by any firm are, rapidly changing customer preferences and competition. The markets demand frequent innovation and higher quality and products have shorter lifecycles (Mclvor and Humphreys, 2004).A firm’s competitive advantage is much short-lived and difficult to maintain in a volatile environment (Biedenbach & Soderholm, 2008). Hence in today’s uncertain times, firms are looking for ways to reduce product-development times while simultaneously improving quality and reducing costs (Yeh et al. 2010). Different organizational capabilities, such as technological, marketing, external and internal integrative capabilities affect NPD process efficiency and new product effectiveness, (Linzalone, 2008).

3. Theory and Research Framework Development

This section draws from the literature of dynamic capability and goes on to develop the research framework identifying the factors of dynamic capabilities to be considered for benchmarking NPD performance along various dimensions.

3.1 Dynamic Capability and NPD Performance

Many firms have realized the importance of the NPD process as a long-term business development activity and are putting more effort into the management of NPD, even then the failure rate of new products is high—with rates of up to 40% having been reported (Cooper and Edgett, 2003). One of the most significant reasons for these high failure rates is the under-utilization of contemporary tools and techniques to aid NPD, (Mohammad Hossein Khasmafkan Nezam, (2013).

An effective new product development program is widely recognized as a source of competitive advantage that firms can depend upon for long term survival. The task becomes even more challenging due to the dynamic nature of the environment (technology, customer preferences, and competitors) and the time scales involved. Companies see NPD as an effective medium through which to practice their strategy. According to Yahaya and Abu-Bakar (2007), NPD practices involve strategic management issues, project management issues, process and structural issues, and people management issues.

Improving the NPD performance requires more efficient and effective NPD processes-primarily by reducing or eliminating wastage of resources on peripheral activities, changes, and reworks (Yeh, Pai, and Yang, 2010). This has led firms to think of more dynamic ways of developing new products (Takeuchi and Nonaka 1986). The concept of DC assumes importance in this context to achieve quick time to market through the ability to respond to new market demands along with the ability to correct mistakes (Menon et al. 2002). Many researchers have proposed the dynamic capability view as a contemporary theory while investigating performance, (Garcı´a- Morales, Ruiz-Moreno, et al., 2007; Kor & Mahoney, 2005; Wu, 2007; Zhang, 2007; Zhu & Kraemer, 2002), especially NPD performance in turbulent environment, (Pavlou and Sawy 2011).So, this study examines the dynamic capability as a means to achieve NPD excellence in uncertain environments through renewing and reconfiguring the NPD processes**.**

According to Moullin, (2003) the organization’s performance is defined as “how well the organization is managed” and “the value the organization delivers for customers and other stakeholders.” Efficiency and effectiveness are two fundamental factors of performance, (Neely, Adams, et al. 2002).The extent to which stakeholder requirements are met is indicated by effectiveness, while efficiency measures how economically the firm’s resources are utilized for providing a given level of stakeholder satisfaction.

The long timescales involved and its intangible nature makes NPD performance difficult to measure and harder to manage. Successful NPD efforts produce multiple benefits (Menor and Roth, 2007) along the financial and non-financial dimensions.

The less innovative firms use solely financial performance measurement, while truly innovative firms employ a number of softer internal dimensions, (Storey and Kelly 2001).Non-financial dimensions of product innovation performance generally consist of speed (time to market), product quality, effectiveness (e.g. the number of new products developed annually), relationship enhancement (e.g. customer loyalty) and corporate reputation (Hsueh*et al*., 2010; Blazevica and Lievens, 2004).

The research proposes to benchmark the dynamic capabilities against the performance of NPD units of the ESDM industry using empirical data employing data envelopment analysis for the first time. It uses the following four dimensions for measurement of NPD performance; competitive performance, customer satisfaction, development cost and development time (Figure 1). To help an NPD manager in decision making, the dynamic capabilities of the NPD unit has to be benchmarked with their peer units against their performance levels. It is also important to understand whether the inefficiency is due to managerial causes or due to the scale of operations (due to employing obsolete or ineffective technologies and processes).

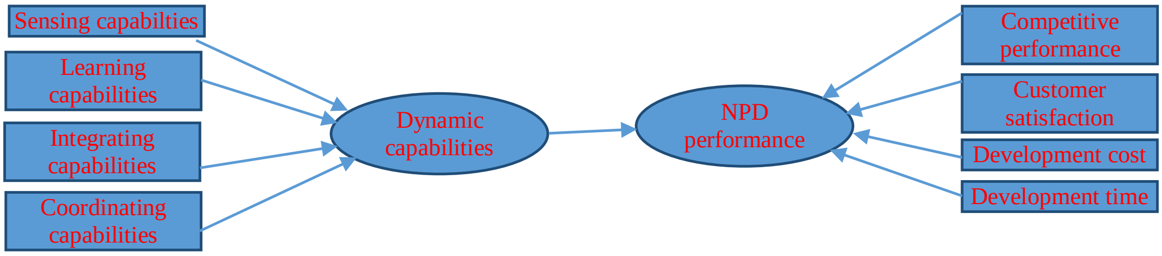

Figure 1 *Dynamic capability – NPD Performance*

An effective model to benchmark NPD performance will give valuable insights into the relations between the dynamic capability levels and NPD performance. There search employs data envelopment analysis (DEA) to help benchmark individual industry performance to its peer units. Major reasons for selection of DEA over other methods is that it does not need a prior model between inputs and outputs, it easily accommodates multiple inputs and multiple outputs, it provides a scalar measure of relative efficiency that helps in target setting by identifying areas of potential addition in outputs and reduction in inputs.

Charnes, Cooper, and Rhodes (1978) put forward DEA as a method for comparing efficiency or benchmarking of similar business units with multiple inputs and multiple outputs where conventional efficiency calculations cannot be applied easily. DEA computes an efficiency frontier based on a non-parametric linear programming technique that optimizes a weighted output-input ratio for each business unit subject to the condition that this ratio can equal but never exceed unity for any other unit in the data set. Application of DEA will help managers to achieve the following: (i) benchmark or measure the relative performance of their NPD units (ii) identify top-performing units among their peers, (iii) identify in what way they can improve their performance.

4. Research Methodology

The research intends to examine the association between dynamic capability and the NPD performance and benchmark the capabilities and NPD performance employing DEA, and hence suitable measures must be developed for these two constructs.

4.1 Population and Sample Size

The survey was conducted among managers and designers associated with the NPD activities in the electronics industries sector identified through memberships with various industry associations. Invitation to participate in the online survey was sent to 397 respondents clearly explaining the purpose of the study and guarantee of anonymity and confidentiality of the data provided. Respondents were instructed to obtain inputs from other members of their NPD units in case they did not have the knowledge of the aspects covered in the instrument. 79 usable responses were received (19.9% response rate) which is generally acceptable in online surveys. There were respondents with 5 years to 19 years of experience. Correlation and multiple regression analyses were conducted on the data to find the association of DC with NPD performance.

DEA was done on the responses from 30 NPD units selected at random. Input oriented efficiency scores are computed using CCR and BCC models with four dimensions of DC as inputs and 4 dimensions of performance as outputs. According to Cooper et al, (2007), two rules for estimating the sample size for DEA study is jointly expressed as $n \geq max\{m * s; 3(m+s)\}$ $where\ n = number\ of\ NPD\ units, m = number\ of\ inputs\ and\ s = number\ of\ outputs.$ Since m=4 and s=4 the sample size of 30 is greater than the desired value suggested by the rule of thumb (24) to give sufficient discriminatory power for DEA.

4.2 Research Instrument Development

The study uses constructs that are operationalized through items sourced from literature. The items were adapted to NPD units and worded to bring out the relative ratings among the peer units. The dynamic capability uses a formative model made up of four factors that are measurable. Generation, dissemination, and responsiveness to market intelligence is measured through sensing capability (Jaworski & Kohli, 1993), acquisition, assimilation, transformation and exploitation of knowledge measured through learning capability (Cohen & Levinthal, 1990; Zahra & George, 2002), contribution, representation, and interrelation of individual input to entire business unit measured through integrating capability (Weick & Roberts, 1993) and resource allocation, task assignment and synchronisation captured through coordinating capability (Crowston, 1997). These four constructs are operationalized through 19 items (Pavlou and Sawy, 2011).

Measurement for NPD performance uses a formative model employing 15 items covering four constructs; customer satisfaction, competitive performance, development cost and development time, (de Brentani 1989, Voss (1992 cited in Johne and Storey 1998, Tatikonda, Mohan. V. 2008).

In this study, we used perceptive scales due to the non-availability of archival data. According to Song et al., (2005) subjective scales allow meaningful comparison across firms and hence it is well suited for the purpose of benchmarking capabilities and computation of relative efficiencies. A five-point Likert scale of measurement (5 = strongly agree, 4= agree, 3 = neutral, 2= disagree, 1 = strongly disagree) is used for capability constructs and for performance factors, the items scale from 1-5 was used (5 = far above industry average, 4= above industry average, 3 same as industry average, 2= below industry average, 1 = far below industry average). The survey instrument was fine-tuned with inputs from experts in the field.

4.3 Data Envelopment Analysis

For applying DEA, the study employs constant returns to scale CCR model which is basically a problem that tries to maximize the ratio of weighted multiple outputs to weighted multiple inputs, subject to the condition that none of the peer units in the data set has an efficiency of more than unity. Among a set of NPD units, the DEA helps to identify a set of optimally performing units and assigns them a score of unity. These NPD units form the efficiency frontier or data envelope against which other NPD units are compared. Those units which require relatively more weighted inputs to produce the same weighted outputs or less weighted outputs for the same weighted inputs are termed inefficient and assigned efficiency values of less than one. The DEA also provides information on efficiency reference sets (ERS) for inefficient units. ERS are those units against which the inefficient units are found to be most directly inefficient. Managers can try to adopt the best practices followed in these ERS for improving the performance of inefficient units.

The first step in the benchmarking is the calculation of technical, pure technical and scale efficiency scores of NPD units by employing the CCR and BCC models involving 4 dimensions of dynamic capabilities as the inputs and NPD performance dimensions as outputs. A measure of technical efficiency under the assumption of constant returns to scale (CRS) is known as overall technical efficiency (OTE). The OTE accounts for the inefficiencies due to the input/output configuration or size of the operations. DEA further breaks down the OTE into two mutually exclusive and non-additive components: pure technical efficiency (PTE) and scale efficiency (SE). This decomposition allows the managers to get a better understanding of the source of inefficiencies. PTE is computed by estimating the efficient frontier under the assumption of variable-returns-to-scale (VRS). PTE is a measure of TE without the effect of the scale of operations and purely reflects the managerial performance in organizing the inputs for getting the desired outputs. Hence PTE can be used as an effective indicator of managerial performance. Scale efficiency is computed by the ratio of OTE to PTE and is an indication of the efficiency resulting from the scale of operations. In other words, the inappropriate level of capability (too low or too high or employing poor technologies and in-effective processes) may sometimes be a cause of technical inefficiency referred to as scale inefficiency. Depending on the current scale of operation the scale inefficiency can be of two forms: decreasing returns to scale (DRS) or increasing returns to scale (IRS). DRS implies that the scale of operation of the NPD unit (capability level) is too high to take full advantage of the capability level (or maybe creating too frequent changes in operational capability thereby disrupting their efficiency) and has supra-optimum capability level. In contrast, a unit experiencing IRS has a scale of operation (capability level) that is too small for efficiency. An NPD unit is scale efficient (at optimum capability level) if it operates at constant returns-to-scale (CRS).

In DEA, the TE can be viewed from two angles. Input orientation explores the possibility of reducing inputs while producing the output at the same levels. In the context of NPD units, how to achieve the same NPD performance with lower dynamic capability levels, i.e dynamic capability levels just sufficient to maintain adaptability without creating too frequent changes in processes and routines that will disrupt the efficiencies and thereby reducing the performance. The efficiency measure of NPD unit can be expressed as

$$\theta_{input} = \frac{Minimum\ possible\ input}{Actual\ input}$$

On the contrary, output-oriented TE tries to increase the outputs for a given level of inputs. In the NPD units context, how to improve the NPD performance for a given level of dynamic capability

$$\theta_{output} = \frac{Actual\ output}{Maximum\ possible\ output}$$

The expression used for computing the technical efficiency (TE) scores of NPD units under different scale assumptions is as follows:-

Minimize

1. $TE_o = \theta_o - \varepsilon[\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+]$

Subject to

2. $\sum_{j=1}^{n} \gamma_j x_{ij} + S_i^- = \theta_o X_{io}$
3. $\sum_{j=1}^{n} \gamma_j Y_{rj} - S_r^+ = Y_{ro}$

4. $S_i^-, S_r^+ \geq 0 \; (i = 1, \dots m; \; r = 1, \dots\dots s)$
5. $\gamma_j \geq 0, if\ constant\ return\ to\ scale$
6. $\sum_{j=1}^{n} \gamma_j = 1, if\ variable\ return\ to\ scale$

Where

$X_{io} = amount\ of\ input\ i\ used\ by\ NPD\ unit\ o$

$Y_{ro} = amount\ of\ output\ r\ produced\ by\ NPd\ unit\ o$

m = number of inputs, s = number of outputs

n = number of NPD units and ε is a small positive number.

$S_i^-\ is\ input\ slack\ and\ S_r^+ is\ output\ slack$

The above model involving i) to v) estimates Farrell's input-oriented TE under the assumption of constant returns to scale. The efficiency estimate provided by the above CCR model is known as overall technical efficiency (OTE). The model involving i) – iv) and vi) estimates Farrell's input-oriented efficiency measure under the assumption of variable returns to scale. The above model known as the BCC model estimates pure technical efficiency (PTE). The ratio of OTE to PTE gives scale efficiency. Further, the nature of returns to scale can be determined from the magnitude of optimal $\sum_{j=1}^{n} \gamma_j^*$ in the CCR model. The type of returns to scale can be determined from the following three scenarios listed by Seiford and Zhu (1999):-

1. $\sum_{j=1}^{n} \gamma_j^* = 1, for\ any\ alternate\ optima\ indicates\ a\ CRS\ situation$
2. $\sum_{j=1}^{n} \gamma_j^* < 1, for\ any\ alternate\ optima\ indicates\ a\ IRS\ situation$
3. $\sum_{j=1}^{n} \gamma_j^* > 1, for\ any\ alternate\ optima\ indiates\ a\ DRS\ situation$

The results of DEA represented by the above models can be interpreted as follows:-

$\theta_o^* = 1$ for any NPD unit that is on the efficient frontier. If $\theta_o^* < 1$, then the NPD unit is inefficient and can either reduce input levels or increase output levels to improve efficiency.

The LHS of constraints ii) and iii) provides the "reference set" for the unit under evaluation given in RHS. The non-zero optimal γ_j^* represents the specific benchmarks for the unit under consideration. The reference set gives the coefficients(γ_j^*) to define a hypothetical efficient NPD unit.

Inefficient NPD units can improve efficiency by setting targets for inputs and outputs as $\hat{X}_{io} = \theta_o^* X_{io} - S_i^{-*}\ and\ \hat{Y}_{ro} = Y_{ro} + S_r^{+*}$ respectively.

5. Data Analysis and Empirical Results

The first step in data analysis is the assessment of the validity and reliability of the constructs, followed by examining the relationship between dependent variables and independent variables before application of DEA for estimating relative efficiencies. The efficiencies are further broken down into PTE and SE along with the finding of target values through slack analysis employing appropriate software. The data analysis is done using SPSS package version 20.0 and DEA is done with DEA Solver LV 8.0.

5.1 Validity and reliability

Even though all the items of various constructs used in the instrument are sourced from literature, the content validity is further ensured by closely examining the measurement method and the individual items against the conceptual definition of the constructs. This was followed by Confirmatory Factor Analysis (CFA) and some of the items which were showing significant cross-loadings were eliminated to improve the model.

Construct validity is assessed through convergent validity and discriminant validity (Campbell and Fiske, 1959). According to the Fornell-Larcker (1981) criteria, for validity, the average variance extracted (AVE) for the constructs should be > 0.6 and the composite reliability (CR) should be > 0.7.

Table 1 *Observations - Validity and Reliability Parameters*

Constructs	Items	Factor loading	Cronbach's alpha	CR	AVE
Dynamic capability(DC)	Sensing capability (SC)	0.697	0.791	0.808	0.627
	Learning capability (LC)	0.847			
	Integrating capability (IC)	0.782			
	Coordinating capability (CC)	0.832			
NPD performance	Competitive Performance (CP)	0.928	0.884	0.912	0.770
	Customer Satisfaction (CS)	0.887			
	Development cost (DCST)	0.834			
	Development time (DT)	0.859			

The observations on the above parameters for all items and constructs and are found to be complying with the requirement for convergent validity, CR >0.7, AVE > 0.6 as given in Table 1. The reliability of individual items is examined through their factor loadings and Cronbach's alpha. Cronbach's alpha and factor loading of all items are found to be > 0.7. Cronbach's alpha for the overall instrument is 0.836 showing strong internal consistency.

Similarly, for discriminant validity, the Fornell-Larcker (1981) test requires that the square root of the AVE for each construct should be greater than the correlation involving the constructs. The results of discriminant validity observations are given in Table 2. The bold terms on the diagonal indicate the square root of AVE and other terms indicate the correlation between the respective constructs. The two constructs are found to comply with the requirement for discriminant validity.

Table 2 *Discriminant Validity*

Constructs	Dynamic capability	NPD performance
Dynamic capability	**0.791**	
NPD performance	0.366	**0.877**

The result of the Kaiser Meyer Olkin (KMO) test for sampling adequacy for the measurement model is 0.689 indicating the adequacy of the sample (> 0.6). Similarly, Bartlett's test for Sphericity reported an approximate Chi-Square value of 467.122, d.f of 28 and Significance of 0.000 (Table 3) hence the null hypothesis that the correlation matrix is an identity matrix is rejected indicating that there is scope for dimension reduction or factor analysis.

Table 3 *Measurement of Sampling Adequacy*

KMO test for sampling adequacy	Bartlett's test for sphericity	
0.689	Approximate Chi-Square	467.122
	d.f	28
	Significance	0.000

5.2 Correlation and Regression Results

Table 1 gives the results of the correlation between various factors. The DC and the four NPD performance dimensions were analyzed and it is found that there is a significant correlation between all the NPD performance dimensions and DCexcept for the development cost.

Table 4 *Correlation between DC and NPD Performance*

		CP	CS	DCST	DT
DC	Pearson Correlation	.499**	.412**	.161	.370**
	Sig. (2-tailed)	.000	.000	.157	.001
**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed). DC-dynamic capability, CP-competitive performance, CS-customer satisfaction, DCST-development cost, DT-development time					

The association between the four components of DC and the NPD performance dimensions are also examined by conducting multiple regression analysis. Analysis results show that the relationships between DC components and all the four NPD performance dimensions are statistically significant. However, the adjusted R square values are greater than 0.4 only in the case of Competitive performance (CP) and customer satisfaction (CS), 0.583 and 0.449 as given in Table 5.

Table 5 *Multiple Regression Results DC- NPD Performance*

		ANOVA		
NPD performance	DC components (statistically significant t-value)	F	Significance	Adjusted R^2
Competitive performance	SC, LC, IC, CC	28.246	0.000	0.583
Customer satisfaction	SC, LC, IC	22.192	0.000	0.449
Development cost	LC, IC	15.102	0.000	0.266
Development time	LC, CC	13.198	0.000	0.238
SC- sensing capability, LC- learning capability, IC- integrating capability, CC- coordinating capability				

The purpose of designing this benchmarking model is to evaluate the relative performance of NPD units in a comprehensive way from the dynamic capability perspective and to provide usable results to decision-makers. For DEA, the selection of outputs is done to reflect the major objective of the organization under study (Chen and Chen, 2007).Hence for this study, from the theoretical framework and also based on the results of correlation and multiple regression as given above, it is decided to include the sensing capability, learning capability, integrating capability, and coordinating capability as the inputs variables and, competitive performance, customer satisfaction, development cost, and development time as the output variables for benchmarking the NPD performance.

Table 6 gives the descriptive statistics of the DEA. The results show that out of the 30 NPD units analyzed, 7 are found to be efficient and the remaining 23 are operating at <100% efficiency levels and are termed as inefficient NPD units. The analysis shows that the OTEs of the NPD units vary from a minimum of 67.76% to 100%.The Average OTE score of 89.84% indicates that on average, the NPD units can improve their efficiency by 10.16% if operating on their efficient frontier instead of its current operating point. The table also indicates the quartiles for the purpose of the classification of the units. Similarly, the descriptive statistics of the 23 inefficient units reveal that the average overall technical inefficiency figure is 13.25% indicating that there is a scope of improvement inefficiencies.

Table 6 *Descriptive Statistics- Overall Technical Efficiencies, Pure TEs and Scale Efficiencies of NPDUs*

Statistics	OTEs	PTEs	SEs	OTEs (inefficient NPDUs)
N	30	30	30	23
Average	0.8984	0.9245	0.9711	0.8675
SD	0.0923	0.0777	0.0449	0.0833
Min	0.6776	0.7346	0.7810	0.6776
Q1	0.8652	0.8927	0.9681	0.8004
Median	0.9175	0.9369	0.9824	0.8880
Q3	0.9063	1.0000	0.9988	0.8880
Maximum	1.0000	1.0000	1.0000	0.9908
Average inefficiency %	10.1577	7.5480	2.8895	13.2491

5.3 Discrimination of Efficient NPD Units

Table 7 gives the OTE scores of individual NPD units along with the efficiency reference sets (ERS). There are 7 NPD units which are having an OTE score of 1, which implies they are operating in the efficient frontier. Chen (1997) and Chen and Yeh (1998) suggested the use of frequency in the 'reference set' to discriminate efficient units. If an NPD unit shows up more frequently in the efficiency reference sets of inefficient units it implies that this unit is more robust than other efficient units. Or in other words, this unit is efficient in more number of factors than other efficient units and is more likely to remain efficient unless there are some major changes in the internal or external environment.

Table 7 *OTE Scores and Reference Sets - CCR*

DMU	Score	Rank		Reference(Lambda)								
U1	1	1	U1	1								
U2	0.9266	13	U1	0.082	U13	0.544	U26	0.119	U28	0.408		
U3	1	1	U3	1								
U4	0.8954	17	U1	0.118	U3	0.396	U13	0.016	U28	0.378		
U5	0.8866	20	U13	0.406	U26	0.198	U28	0.447				
U6	0.9326	12	U1	0.103	U3	0.503	U13	0.51	U28	0.008		
U7	0.8809	21	U1	0.043	U13	0.334	U26	0.153	U28	0.558	U30	0.005
U8	0.9446	10	U3	0.171	U13	0.543	U26	0.124	U28	0.232		
U9	0.6776	30	U13	0.155	U26	0.087	U28	0.417				
U10	0.8788	22	U13	0.382	U26	0.16	U28	0.554				
U11	0.8913	18	U1	0.229	U13	0.524	U26	0.083	U28	0.191		
U12	0.9171	16	U13	0.224	U26	0.123	U28	0.709				
U13	1	1	U13	1								
U14	0.9446	10	U3	0.171	U13	0.543	U26	0.124	U28	0.232		
U15	0.9229	14	U1	0.106	U13	0.706	U26	0.378	U28	0.008		
U16	1	1	U16	1								
U17	0.8032	24	U1	0.444	U3	0.203	U26	0.118	U28	0.188		
U18	0.888	19	U1	0.073	U13	0.485	U26	0.179	U28	0.399		
U19	0.7941	26	U1	0.824	U26	0.176						
U20	0.7447	28	U1	0.12	U3	0.075	U13	0.422	U26	0.301	U28	0.027
U21	0.7777	27	U13	0.065	U26	0.175	U28	0.476				
U22	0.7129	29	U13	0.818	U26	0.145						
U23	0.9663	9	U1	0.307	U13	0.767	U26	0.141				
U24	0.8606	23	U1	0.037	U13	0.76	U26	0.296				
U25	0.7975	25	U1	0.536	U26	0.31	U30	0.114				
U26	1	1	U26	1								
U27	0.9908	8	U13	1.084	U26	0.076	U28	0.036	U30	0.108		
U28	1	1	U28	1								
U29	0.9179	15	U13	0.803	U26	0.386	U28	0.012				
U30	1	1	U30	1								

From the data given in table 7, the leaders (efficient units), followers (inefficient units) and the rank among the efficient units (super efficiency) can be found out. NPD unit designated as U26 is the most frequently occurring unit in the ERS with

21 occurrences out of possible 23 and is ranked 1 followed by U13 with 20 occurrences. The NPD unit 16 even though with efficiency 1 does not occur even once in the ERS. The NPD units with rare occurrences in the ERS are most likely to possess a very uncommon input-output mix and are not good models to emulate. Based on the frequency of occurrence, these efficient NPD units can be further categorized into highly efficient and marginally efficient units. The marginally efficient units may slip from the efficient frontier with a small change in the operating condition to inefficient category and hence have to work on improving their processes to sustain efficiency.

5.4 Discrimination of Inefficient NPD Units

Among the 23 inefficient NPD units, the efficiency figures vary from a minimum of 67.76% for U9 to a maximum of 99.08% for U27 as given in Table 8.

Table 8 *Types of Efficiencies and Inefficiencies*

No.	DMU	OTE	PTE	SE	Inefficiency	Sum Lambda	RTS
1	U1	1	1	1.0000		1	CRS
2	U2	0.9266	1	0.9266	S	1.153	DRS
3	U3	1	1	1.0000		1	CRS
4	U4	0.8954	0.9191	0.9742	M	0.908	IRS
5	U5	0.8866	0.8951	0.9905	M	1.051	DRS
6	U6	0.9326	0.9708	0.9607	S	1.124	DRS
7	U7	0.8809	0.8923	0.9872	M	1.088	DRS
8	U8	0.9446	0.9722	0.9716	S	1.07	DRS
9	U9	0.6776	0.8676	0.7810	S	0.659	IRS
10	U10	0.8788	0.8923	0.9849	M	1.096	DRS
11	U11	0.8913	0.8955	0.9953	M	1.027	DRS
12	U12	0.9171	0.923	0.9936	M	1.056	DRS
13	U13	1	1	1.0000		1	CRS
14	U14	0.9446	0.9722	0.9716	S	1.07	DRS
15	U15	0.9229	0.9508	0.9707	M	1.198	DRS
16	U16	1	1	1.0000		1	CRS
17	U17	0.8032	0.8098	0.9918	M	0.953	IRS
18	U18	0.888	0.9062	0.9799	M	1.136	DRS
19	U19	0.7941	0.7941	1.0000	M	1	CRS
20	U20	0.7447	0.7699	0.9673	M	0.918	IRS
21	U21	0.7777	0.8939	0.8700	S	0.716	IRS
22	U22	0.7129	0.7346	0.9705	M	0.963	IRS
23	U23	0.9663	1	0.9663	S	1.215	DRS
24	U24	0.8606	0.9069	0.9489	M	1.093	DRS
25	U25	0.7975	0.8185	0.9743	M	0.96	IRS
26	U26	1	1	1.0000		1	CRS
27	U27	0.9908	1	0.9908	S	1.304	DRS
28	U28	1	1	1.0000		1	CRS
29	U29	0.9179	0.9508	0.9654	M	1.201	DRS
30	U30	1	1	1.0000		1	CRS

Since the quantum of management intervention required for each of them is not the same, they are further divided into 4 categories based on below which quartile (Table 6) their OTE lie. The inefficient units can be classified into "most inefficient" units whose OTE fall below the 1st quartile, "below average" whose efficiency fall below the 2nd quartile (median), "above average" whose efficiency fall below 3rd quartile and "marginally inefficient" whose efficiency fall above 3rd quartile.

This categorization helps to focus the improvement efforts. The NPD units in the most inefficient category are the probable candidates for any improvement efforts and may yield better results as they are operating at lower efficiencies. Similarly, the units in the marginally inefficient category are also important as these units can be moved to the efficiency frontier with a little improvement effort.

5.5 Decomposing OTE into Managerial and Scale Efficiency

To understand the nature of inefficiency, whether due to managerial underperformance or due to scale of operation, the OTE has to be further decomposed into PTE (managerial efficiency) and SE (Scale efficiency – due to employing of poor technologies and in-effective processes). PTE is estimated from the BCC model under the assumption of VRS which removes the effects due to the scale of operation.

Since the efficiency frontier estimated under the assumption of VRS envelopes the data points more closely than the CCR model, the efficiency figures under the assumption of VRS will be equal to or greater than that obtained under the CRS assumption. The units attaining OTE and PTE scores of 1 are designated as “globally efficient” and locally efficient” respectively in DEA literature.

The descriptive statistics about PTEs and SEs estimated under the VRS assumption is given in table 3. It can be seen that out of 10.15 % of average inefficiency, 7.55% is contributed by managerial underperformance and only 2.89% is contributed by efficiency resulting from the scale of operation. From the individual efficiency estimates given in table 8, it is observed that out of 23 inefficient units, 15 (65%) are the results of managerial underperformance and only 8 (34.7%) are due to employing of poor technologies and in-effective processes (scale of operations) as shown in Figure 2.

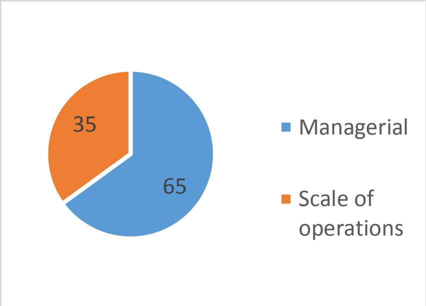

Figure 2 *DC- NPD Performance Inefficiencies*

Table 5 also gives the type of return to scale determined by the expressions a), b), and c). Out of 30 NPD units, 8 are operating in CRS, 23 are operating in DRS and 7 are operating in the IRS type return to scale. The units operating under IRS can improve their efficiency by increasing the scale of operations and those with DRS can scale down their operations to improve their efficiency. Unit 19 is operating in CRS but still has OTE of 79.4%, PTE of 79.4% and SE of 100%, this means that unit 19 is operating at optimal scale but the lower OTE is due to managerial underperformance.

5.6 Areas of Managerial Intervention- Analysis of Slacks and Target Setting

Table 9 gives the slacks computed by DEA for inputs and output variables. Scrutiny of the table reveals that the slacks are present only for inefficient units. Slacks provide vital information helpful for managerial intervention targeting efficiency improvements. The slacks represent the additional changes required at the inputs or outputs (reduction in inputs or enhancement of outputs) to reach efficiency frontier. After the proportional reduction in inputs, if an NPD unit cannot reach the efficiency frontier, the slacks are required to push the units to their targets (Ozcan, 2008).

Since the model is input-oriented, input slacks indicate the amount by which inputs are excess and output slacks indicate the amount by which outputs can be increased. For a better understanding of the interpretation of slacks and target setting, consider the case of NPD unit 9 which is relatively the most inefficient unit with an OTE of 67.76%. This implies that to become technically efficient 1st thing unit 9 has to do is to reduce all its inputs by 32.24% (i.e. 1-OTE). Even reducing all the inputs proportionately may not guarantee that the NPD unit is operating in the Pareto-efficient point as indicated by the presence of non-zero slack. The slack for the input variable *sensing capability (SC)* has a value of 0. The next row titled as projection indicates that to reach the efficiency frontier, the NPD unit 9 has to reduce its input SC by 32.24%. The next input *learning capability (LC)* has a slack of 3.047 and the projection indicates that LC input has to be reduced to 44.43% including the 32.24% common to all inputs to reach the efficiency frontier. Similarly, the IC input has to be reduced to 33% and input CC has to be reduced by 32.24%. The results are summarized in figure 3. The presence of output slacks indicates that to reach the Pareto-efficient operating point, NPD unit 9 has to enhance the output CP by 3.34%, and output CS by 2.56%. In summary, this implies that even though unit 9 reports a high level of DC, its efficiency is not the same as that of the best-in-class leader -it may be due to the use of obsolete or inefficient processes and hence the need to intervene to improve the effectiveness.

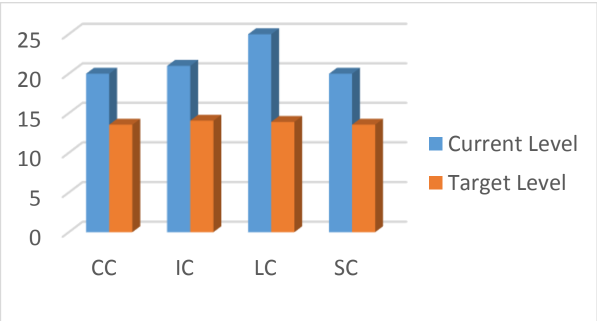

Figure 3 *Dynamic capability levels DMU 9*

Similarly, predictions can be made for the survey group as a whole. Since the average OTE is 89.84%, all the inputs have to be proportionately reduced by 10.16% and in addition, the LC has to be further reduced by 13.4%, that of IC has to be reduced by 13%. As far as the outputs are concerned, to reach the efficiency frontier the CP has to be increased by 5%, CS by 3.8%, DCST by 21.5% and DT by 27.6%.

Table 9 *Input-Output Slacks*

			Slack	**Slack**	**Slack**	**Slack**	**Slack**	**Slack**	**Slack**	**Slack**
DMU	Score	Rank	SC	LC	IC	CC	CP	CS	DCST	DT
U1	1	1	0	0	0	0	0	0	0	0
U2	0.9266	13	0	1.69	1.637	0	0	0	2.508	0
U3	1	1	0	0	0	0	0	0	0	0
U4	0.8954	17	0	0.274	0	0	2.005	0	0	0.055
U5	0.8866	20	0	0	0.147	0	0	0.445	5.554	6.108
U6	0.9326	12	0	1.014	0	0	1.503	0	0	3.489
U7	0.8809	21	0	0	0	0	0	0	5.429	0.66
U8	0.9446	10	0	0.201	0	0	3.012	4.424	0	0
U9	0.6776	30	0	3.047	0.182	0	0.401	0.385	0	0
U10	0.8788	22	0	0.074	0	0	0	1.714	2.425	2.732
U11	0.8913	18	0	0	0.06	0	0	0	2.369	0.952
U12	0.9171	16	0	0.339	0	0	0	3.832	2.574	2.459
U13	1	1	0	0	0	0	0	0	0	0
U14	0.9446	10	0	0.201	0	0	3.012	4.424	0	0
U15	0.9229	14	0	0	3.895	0	0	0	1.69	3.522
U16	1	1	0	0	0	0	0	0	0	0
U17	0.8032	24	0	1.846	0	0	0.472	0	0	2.355
U18	0.888	19	0	0	1.025	0	0	0	2.342	2.965
U19	0.7941	26	0	1.882	1.618	0	0.706	0	0	0.529
U20	0.7447	28	0	0	2.217	0	0.013	0	0	0
U21	0.7777	27	0	0	0.05	0	0	1.451	1.958	4.073
U22	0.7129	29	0	2.931	3.366	0	3.182	3.363	1.746	0
U23	0.9663	9	0	4.899	0.491	0	3.233	0	7.81	0
U24	0.8606	23	0	1.58	3.328	0	1.907	0	0.353	0
U25	0.7975	25	0	0	0.825	0	2.371	0	1.719	2.535
U26	1	1	0	0	0	0	0	0	0	0
U27	0.9908	8	0	3.586	0	0	0	0	2.906	5.073
U28	1	1	0	0	0	0	0	0	0	0
U29	0.9179	15	0	0	1.145	0	0	0.398	8.642	12.591
U30	1	1	0	0	0	0	0	0	0	0

6. Conclusion

The value of the study lies in the application of DEA to benchmark the dynamic capabilities of NPD units in the ESDM sector. This paper focused on examining the factors affecting the performance of the NPD units and a method to compare the relative efficiencies of peer units. It employed a cross-sectional mail survey among NPD units in the Indian ESDM sector to suggest ways to achieve excellence in new product development in an uncertain and changing environment.

The research makes at least three contributions to the dynamic capabilities literature. First and foremost, it is the first time that the DEA methodology was employed for benchmarking the performance of the NPD units in the ESDM sector in the context of dynamic capabilities. While DEA has been employed for performance comparison in various sectors like hospital services, banks, hotels, manufacturing, etc., very few researchers have used DEA in the context of R&D organizations (Jyoti et al., 2008) and none in the context of dynamic capabilities and NPD performance. Jyoti et al., (2008) has applied DEA for R&D organizations in chemical and botanical sciences and employed seven pre weighted objective measures as inputs and outputs (annual budget as input, and six outputs consisting of papers published, number of patents, number of products, number of awards, number of PhDs and external revenue generated) and suggests inclusion of subjective measures for further research. Trappey et al., (2007) has employed DEA for developing a project planning and management decision support methodology for NPD that can optimally allocate resources and dynamically respond to unexpected delays and budget overruns.

Second, the study provides a comprehensive method to policymakers and NPD managers for evaluating the performance of NPD units in terms of their relative efficiencies. Firms measure NPD performance along many different dimensions including customer satisfaction, competitive performance, development time, development cost, and product cost, etc. The priorities of each of these dimensions may be different for different units according to their business strategies. Hence comparing different NPD units in terms of performance is a complex task. Apart from giving a clear picture of where the NPD unit stands in relation to the best-in-class, following the suggestions of Pavlou et al. (2011) the research finds a method whose results can be used for arriving at optimal levels of dynamic capabilities for improved performance. Firms are also classified based on their relative efficiencies and the firms with low relative efficiencies can take up immediate intervention to improve performance.

Third, this paper empirically validates the concept that dynamic capability impacts the performance of the NPD unit in the electronics sector. The above concept is validated based on the responses collected from 79 NPD units from the electronics industry. Results reported statistically significant correlations between dynamic capabilities and NPD performance.

This paper employs DEA to answer the perpetual problems faced by every NPD manager; “how their NPD unit is performing with respect to competition?”, “What can we do to improve our performance to become best-in-class?”. To help an NPD manager in decision making, the study presents a method for benchmarking the dynamic capabilities of the NPD unit with their peer units against their performance levels. It also helps to understand whether the inefficiency is due to managerial causes or due to scale of operations (employing of poor technologies and in-effective processes/capability levels) and suggests specific managerial interventions that would be effective in the form of targets for various factors.

7. Limitations and Scope for Future Research

This section discusses certain limitations of the study which opens up avenues for future research. First, the study has assumed that all the NPD units among the electronics industry are subject to similar environmental dynamism, but it may not be true always. Hence further studies can be conducted among much more uniform categories of NPD units operating under more uniform environmental dynamism in terms of fast-changing technologies and customer preferences and suggest an optimum capability that would be ideal for a given industry or in relation to a given environmental dynamism.

Like many perception-based studies, the data obtained may be subjected to respondent’s biases, like social desirability bias which refers to respondent’s over-reporting of admirable attributes or under-reporting those that are not socially respectable (Krosnick, 1999). To minimize the issue of social desirability bias, the survey was conducted by email explaining the purpose of the survey and assuring that their responses would be kept strictly confidential and all the results would be reported in total without revealing the details of the firm. The fact that the respondents were experienced and knowledgeable and the reasonable response rate of 19.9% obtained considering the profile of the target audience indicates less likelihood for the issue.

The study did not factor in the involvement of any “time element” between dynamic capability and the NPD performance. To factor in the time element resulting from evolving capability levels, a longitudinal study may be conducted among a few firms to check on the effect of change in dynamic capability levels of the same firm in various NPD projects they have undertaken.

To establish actual causation, further research may attempt to collect quantitative data from a few specific NPD projects which specifically attempted improvement of certain NPD performance parameters like development time and the success rate of these efforts based on the strategic and operational capabilities of the firm.

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