# A Resource Allocation Model for Higher Education Based on The Combination of Efficiency Measurement and Market Position Mapping

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## Abstract

This study aimed to develop a method for prioritizing resource allocation at universities based on the results of measuring resource efficiency and the market position of study programs. The efficiency was measured using the Data Envelopment Analysis (DEA) method, followed by mapping the market position of the study program using the growth-share matrix (Boston Consulting Group/BCG) and the GE McKinsey matrix. Those methods were combined to create a priority order for allocating organizational resources. The objects of this research were 12 undergraduate programs as the Decision Making Unit (DMU) at the Engineering Faculty of Diponegoro University. The efficiency measurement result showed that five departments were inefficient: Civil Engineering, Urban and Regional Planning, Electrical Engineering, and Geodetic Engineering. Based on market position mapping results, Industrial Engineering and Urban and Regional Planning were categorized as stars. Computer Engineering, Environmental Engineering, Electrical Engineering, Mechanical Engineering, and Geodetic Engineering were classified as question mark categories. The remaining department, Geological Engineering and Marine Engineering were denoted by lose category. The integration of the DEA method with BCG and GE McKinsey matrix to determine resource allocation matrix based on efficiency and market position was the scientific contribution of this study. The research was conducted based on a business perspective, with the university as a profit institution and the study program as a business unit. This research is intriguing because the indicators used to measure efficiency in a higher education institution are very different from those of a business organization.

## Keywords
Resource Allocation, University, Data Envelopment Analysis, Market Portfolio Matrix.

## 1. Introduction
Nowadays, in the age of a knowledge-based economy, universities have a vital role in developing a country. The primary goal of the university is to explore and disseminate knowledge. It can be achieved by advancing research, teaching, and learning activities between lecturers and students (Kao and Hung 2006). The public universities, most of their funding comes from the state budget, must be able to offer the best value for money. Resource allocation and usage efficiency are two essential points that are interrelated in evaluating the use of resources in a university (Visbal-Cadavid et al. 2017). The university resources are human, financial, and material or tools that support university

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activities (Syahrizal 2008). Those activities carried out by the university are required to be more efficient, effective, and productive (Agasisti 2017).

Public universities in Colombia are ranked according to their efficiency (Visbal-Cadavid et al. 2017). Efficiency measurement for universities is done to determine how well the use of resources, the amount of output produced, and the management process (Gökşen et al. 2015). The Data Envelopment Analysis (DEA) method is an efficiency evaluation tool to measure the relative performance based on comparing several work units. DEA is widely used by several studies and is considered a powerful method (Iribarren et al. 2014; Tao et al. 2013; Amirteimoori et al. 2013).

Besides efficiency, the priority of resource allocation should also be considered while allocating resources. If there is no resource allocation priority, the resources will be distributed according to the previous year's list of needs from each study program or by dividing resources linearly with the student body in each study program. Limited and scarcity of resources force organizations to optimize the use of resources in organizational development (Taha 2007). Long-established study programs have a large number of accumulated production assets, both in human resources and physical assets. On the other hand, new study programs have limited assets, despite that these new study programs require funding to develop. If the linear technique based on the student body is used, this new study program will also receive a small number of development funds. If these new study programs prove to be quite popular in the market (high school graduates), they should be prioritized in allocating resources.

One of the contributions of this research is to develop a method of resource allocation in universities using the efficiency level and market prospects as an assessment to determine the resource allocation priority. This market prospect demonstrates the high demand for study programs. In this case, the institution is considered a business organization comprised of numerous business units. One resource allocation method that can be used is portfolio management. There are two portfolio management models that are frequently used in business resource allocation, which are the growth-share matrix (commonly known as the BCG matrix) and the GE McKinsey matrix.

This study aims to provide a method for a university to prioritize the distribution of resources to all study programs based on the results of efficiency measurements and the market position of each study program. The efficiency calculation was done using the Data Envelopment Analysis (DEA), while market position mapping was carried out using portfolio management adapted from the growth-share matrix and GE McKinsey matrix. The expected result was a visualization of the market position of each undergraduate program at the Faculty of Engineering, Diponegoro University, along with its efficiency value. The result was expected to be used by the faculty management in prioritizing resource allocation to the efficient study program with a good market position. The object of this research was 12 study programs at the Faculty of Engineering, Diponegoro University, that applied a resource allocation linear to the student body. The long-established departments in the Faculty of Engineering at Diponegoro University had more physical assets and human resources than the newly established ones. It resulted in departments that were relatively new and demanded by the market having inadequate facilities, making them unable to support the increasing number of new students. There are six factors in choosing higher education, including academics, facilities, campus life, reputation, industry linkage, and access (Puan Rachmadhani et al. 2018).

## 2. Literature Review

### 2.1 Data Envelopment Analysis (DEA)

The efficiency of a company or organization is often interpreted as success in producing the maximum output with the use of existing inputs. According to Ghiselli and Brown (1948), efficiency shows a comparison between output and input. DEA is one of the main techniques used in public and private sectors to evaluate performance in a set of homogeneous production units with many resources and products. DEA has been used to evaluate performance in primary education (Grosskopf et al. 2014; Huguenin 2015). DEA was also applied at the university level (Agasisti and Bianco 2009; Katharaki and Katharakis 2010; Johnes and Johnes 2009). DEA is a nonparametric approach that is basically a development of Linear Programming (LP; Saati et al. 2011). In DEA, the relative efficiency measure of each work unit (called Decision Making Unit/DMU) is defined as the ratio between the number of weighted outputs

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with the number of weighted inputs. This efficiency value is limited between 0 and 1. It reduces several inputs and outputs used into one virtual input and virtual output without considering weighted values.

DEA was first introduced by Charnes et al. (1978) (known as DEA constant return-to-scale/CSR due to the return-to-scale assumptions used). DEA was then redeveloped as a variable return-to-scale/VRS model. BCC or Banker, Charnes dan Cooper is a DEA model that implemented Variable Return to Scale (VRS) (Purwaningsih et al. 2018). DEA can provide a quantitative recommendation regarding aspects and measures that need to be adjusted to increase the efficiency of a unit (Banker et al. 1984). DEA is a collection of concepts and methodologies that have evolved over time including the CRS ratio model (1978), the VRS model (1984), the multiplicative model (1982-1983), and the additive model (1987; Abraham Charnes et al. 1994). DEA has been widely applied in various fields to calculate system efficiency and recommend inefficient variables. The quantitative DEA approach allows users to identify the potential efficiency that can be made to the system by referring to the DMU that is considered the most efficient. Several researches have been conducted in various fields of study, such as energy efficiency (Lin and Wang 2014; Ali Azadeh et al. 2014; A. Azadeh et al. 2015; Wang et al. 2013; Zou et al. 2013; Iribarren et al. 2014), finance (Kwon and Lee 2015; Tao et al. 2013; Tsolas and Charles 2015; Wanke and Barros 2014), and manufacture (Tone and Tsutsui 2014; Amirteimoori et al. 2013; Toloo and Ertay 2014; Mirhedayatian et al. 2014; Lee and Johnson 2014).

In this study, the models that will be discussed are the CRS and VRS models. The CRS model used the constant return-to-scale (CRS) assumption where every addition or subtraction to the input will have a proportional impact on the output (Panwar 2014). The CRS model assumes that the ratio between the addition of inputs and output is the same or constant. Efficiency results using the CRS model calculation are called Global Technical Efficiency (GTE). The efficiency calculation can be formulated as follows:

$$Max\ Z_0 = \sum_{r=1}^{s} u_r y_{r0}$$

*Subject to*

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0;\ \forall j = 1, \ldots, n$$

$$u_r, v_i \geq 0; r = 1, \ldots, s; i = 1, \ldots, m$$

Where:

$Z_0$ = Efficiency of DMU
$u_r$ = Weighted output *r*
$y_{rj}$ = Number of output *r* of DMU *j*
$v_i$ = Weighted input *i*
$x_{ij}$ = Number of input *i* used by DMU *j*

The CRS assumption is suitable only if all DMUs operate at the optimal operational scale. Unbalanced competition, financial limitations, or other factors might cause the company/organization to operate at an unoptimal scale. The VRS model considers return-to-scale variables where a process can have an increasing return-to-scale (increase in output gets higher per added input) or decreasing return-to-scale (increase in output gets lower per added input). The efficiency calculation result using the VRS model is referred as Pure Technical Efficiency (PTE). The formula of efficiency calculated using the VRA model has a slight difference compared with the CRS model, where in the VRA model, there is an addition in constraint:

$$\sum_{j=1}^{n} \lambda_j = 1$$

From efficiency calculation results using CRS and VRA models, the GTE value can be divided by the PTE value to obtain the Scale Efficiency (SE) value. SE value represents how efficiently the scale of operation is carried out. A DMU can be said to be an ineffective work unit even though it is classified as an efficient work unit (based on CRS

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or VRS result calculation) due to its non-optimal size. Therefore, the business unit should focus on increasing the value of scale efficiency and determining whether the business should do up-sizing (if the return-to-scale increases) or down-sizing (if the return-to-scale decreases). The business unit can focus on increasing the value of technical efficiency (Dellnitz et al. 2018).

The input and output variables used in measuring efficiency using the DEA method have a significant impact on the efficiency result obtained. Most of the previous studies that have measured efficiency at universities use the input variables of land area or facilities in the form of buildings and the number of lecturers and staff. The output variables used are the number of graduating students and the number of publications. The Table 1 shows an overview of the inputs and outputs used by previous researchers.

Table 1. Previous Research Overview

| Previous Research | Input Variable | Output Variable |
|---|---|---|
| Nugraha and Noranita (2014) | • Number of lecturers<br>• Research fund allocation | • Number of articles presented at conferences<br>• Number of articles published in journals<br>• Number of funded research |
| Baysal et al. (2006) | • Personnel costs, other current expenditures<br>• Investment expenses<br>• Transfers<br>• Number of faculty members | • Number of undergraduate students<br>• Number of master students<br>• Number of doctoral students<br>• Number of publications |
| Erkoc (2016) | • General budget expenditures<br>• Expenditures out of budget<br>• Number of professors<br>• Number of associate professors<br>• Number of assistant professors<br>• Number of assistant instructors<br>• Number of administrative staff | • Number of publications that take part in indexes<br>• University income<br>• Number of undergraduate students<br>• Number of graduate students from undergraduate degree<br>• Number of postgraduate students<br>• Number of graduate students from postgraduate degree |
| Gökşen et al. (2015) | • Outdoor-indoor area of university<br>• Number of academic staff<br>• Number of administrative staff | • Number of publications<br>• Number of graduate students |

## 2.2 Management Portfolio Matrix

The development of a competitive strategy aims to see the condition of the organization objectively and to anticipate changes due to internal and external factors. Product portfolio management refers to a strategic analysis tool that is widely used in the enterprise strategic planning resource (Wells and Wells 2011). If the competitive strategy is designed and implemented appropriately, then a competitive advantage with optimal support from the existing resources can be achieved (Fitriadi, 2013). The product portfolio has an objective to analyze the present value and potential value of each organization's strategic business unit and to provide recommendations for strategic decision making and resource allocation.

There are two of the most popular product portfolio models. First, the growth-share matrix that is developed by Boston Consulting Group. It is, visually, depicted as a two-by-two matrix which are relative market share (high and low) and relative market growth level (high and low). This matrix divided the business into 4 categories, stars, cash cows, lose, and question marks. Based on Madsen (2017), growth-share matrix provides to managers a popular prescription for allocating resources, such as milking a cow, releasing a lose, investing in a stars, and analyzing question marks. Second, the GE McKinsey matrix was first developed by McKinsey & Company for General Electronic (GE) to help in managing large and complex portfolio where deployment of a growth-share matrix is insufficient. The GE McKinsey matrix uses 2 dimensions in determining business unit position, which is the business unit competitive strength and industry attractiveness. The GE McKinsey matrix, with a few modifications, can be applied to university allocation strategy. In the context of a university, the GE McKinsey matrix's industry attractiveness dimension is defined as market interest in a department. The factors that influence this dimension are the overall market size, market growth, level of competition, etc.

There are several previous studies that implemented portfolio management at the university level. Keelson (2018) implemented the growth-share matrix at the University of Ghana. Sarjono and Kuncoro (2013) also utilized the growth-share matrix on the position of a university against another institution in Indonesia. Wells and Wells (2011) modified the GE McKinsey matrix and adapted its application to the university.

# 3. Methods and Data Collection

## 3.1 Research Framework

The physical assets such as machine, buildings, and human resources are input in productivity measurements, then, if the physical assets contribution or benefits are below the cost of assets (its annually invest and maintenance cost), the assets became a cost driver that make the productivity smaller. This resulted in a significant change in the organization's size and the development of physical asset sharing for several cooperative organizations. Business organization become leaner and more efficient. However, the profit institution frequently has a different perspective than non-profit institution, which do not prioritize efficiency in resource management. This study attempts to take a different perspective by observing that universities should also consider that the use of their resources/assets must produce output with a value greater than asset's value. This study tries to formulate asset allocation method by establishing priorities based on organizational efficiency and market potential. The input and output variables used are still limited because the amount of available data forbids duplication. Further research could use the DEA method and shared growth matrix in a broader context with more variables.

## 3.2 Research Method

This study aims to develop research method alternative for making resource allocation decisions at a faculty with several study programs by examining a business organization's perspective on its business unit. The resource allocation decision making is based on efficiency and prospect value of the business unit in terms of market attractiveness. The market attractiveness of a study program can be measured by the number of registrant's interest. Figure 1 shows the stages in conducting this research to achieve the objectives. Secondary data from Faculty of Engineering at Diponegoro University was used in this study. The information gathered was related to various operational data, performance, and applicant interest from each department and study program within the Faculty of Engineering.

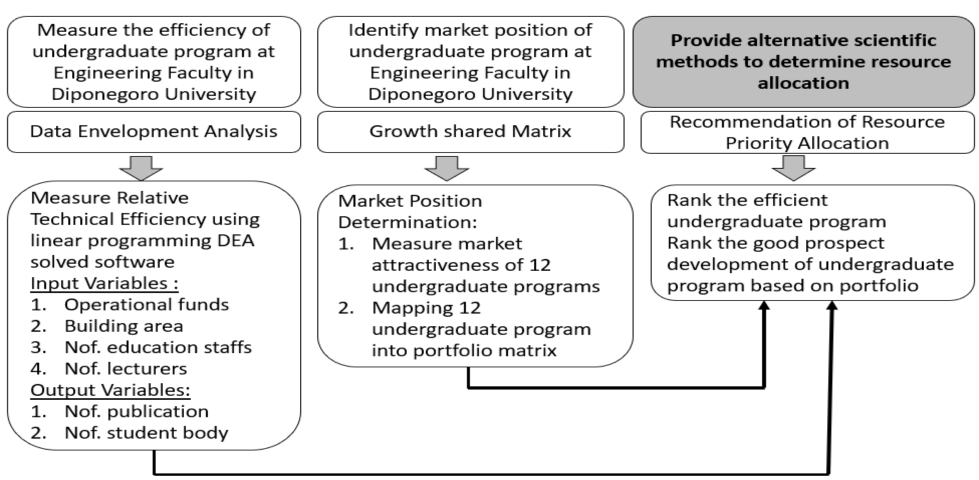


Figure 1. Research Methods

### 3.3 Efficiency Measurement with DEA Method

In measuring efficiency using the DEA method, input and output variables chosen have a significant impact on the efficiency result obtained. These factors, therefore, must be carefully chosen in order to accurately describe the performance of DMU. The variable input of this study would be based on assets ownership and operation aspect over a certain period. Asset aspect owned by each department were assessed based on building area, while the number of lecturers, the number of education staffs, and the usage of fund in a year were used to evaluate the operational aspects. According to Rosenmayer (2014), choosing the output variable in efficiency measurement should be based on the university's goals. The output variables employed in this study were based on two points of the Tri Dharma of University, which were (1) education and (2) research and development. The third Tri Dharma, (3) community services, was not used as an output variable because it was linear allocative to the number of lecturers. The input and output variables that would be used in this study are shown in Table 2. The DMU used in this study was 12 undergraduate programs of Engineering Faculty at Diponegoro University that is shown in Table 3.

Table 2. Input and Output Variables

| Input | Output |
|---|---|
| • Usage of fund in a year (IDR)<br>• Building area ($m^2$)<br>• Number of education staffs (people)<br>• Number of lecturers (people) | • Number of research publication (title)<br>• Number of department student body (people) |

In this study, the measurement of efficiency using DEA was carried out with the help of DEAP/Win4DEAP software so that the value of GTE, PTE, and SE were obtained. The efficiency value that would be used was the GTE value or the CRS model's computation, while the SE value would be used to determine efficiency recommendations. The information used was data in 2020.

### 3.3 Market Position Mapping

Mapping the market position of each department used a product portfolio management tool which were a combination of market position matrix between growth-share and GE McKinsey matrix. Market position portfolio matrix of study program produced was divided based on growth-share matrix into 4 categories. The dimensions of the matrix were followed the GE McKinsey which were the market attractiveness and competitive strength of each department. The market attractiveness of dimension was assessed based on the growth in the number of applicants for new student registrants between years, while the competitive strength dimension was assessed from reputation or admission strictness of each study program. The market attractiveness dimension was calculated using amount of applicants for new student registrants data in 2020, while the competitive strength dimension used data from 2017 to 2020. After obtaining efficiency value from DEA calculation and market position from portfolio matrix, the result would be integrated to generate a market position mapping of 12 undergraduate programs, as well as the result of measuring efficiency. Study programs that were assessed efficient and had a market position in the star and question mark categories were considered worthy to get priority allocation of resources.

## 4. Result and Discussion

### 4.1 Efficiency Measurement using DEA

The input and output data used in this study are describe in Table 3. Result recapitulation of data processing using DEAP/Win4DEAP software are shown in Table 4. Based on Table 4, four departments, namely Department of Civil Engineering, Architecture, Urban and Regional Planning, and Electrical Engineering, were considered inefficient with a decrease return-to-scale. A decrease return-to-scale means that the scale of operations carried out exceeds the optimal size, resulting in each additional input giving a decreasing amount of output. Beside it, there was Geodetic Engineering that was inefficient due to an increase return-to-scale. An increase return-to-scale means that the operational scale has not yet reached the optimal size so that each additional input will still increase the output. This was in line with the practice. The four departments that were stated having a decrease return-to-scale result, Civil Engineering, Architecture, Urban and Regional Planning, and Electrical Engineering, have been established for a long time and had a lot of investment each year in term of the use of annual funds, the building area, and the number of workers. Likewise for Geodetic Engineering that was stated having an increase return-to-scale result, it has limited resources, as evidence by the small building area and few number of human resources, despite that the number of students had increased to equal with other departments. This was a reason why the five departments stated to be an inefficient department.

Table 3. Input and Output Variables Data

| No. | DMU / Department | Usage of Fund in A Year (IDR) | Building Area ($m^2$) | Nof. Education Staffs (People) | Nof. Lecturers (People) | Nof. Reputable Research Publication (Title) | Nof. Department Student Body (People) |
|---|---|---|---|---|---|---|---|
| 1 | Civil Engineering | 1,956,627,275 | 4,417 | 29 | 52 | 140 | 1363 |
| 2 | Architecture | 1,155,285,000 | 4,397 | 16 | 33 | 58 | 748 |
| 3 | Chemical Engineering | 1,383,500,000 | 3,870 | 18 | 38 | 199 | 941 |
| 4 | Urban and Regional Planning | 1,209,676,600 | 2,627 | 15 | 41 | 81 | 805 |
| 5 | Mechanical Engineering | 1,353,800,000 | 3,513 | 15 | 35 | 160 | 899 |
| 6 | Electrical Engineering | 1,164,044,850 | 2,348 | 14 | 32 | 72 | 733 |
| 7 | Marine Engineering | 739,000,000 | 1,238 | 7 | 15 | 17 | 647 |
| 8 | Industrial Engineering | 1,047,947,000 | 3,839 | 10 | 22 | 135 | 768 |
| 9 | Environmental Engineering | 763,400,834 | 1,238 | 10 | 22 | 42 | 512 |
| 10 | Geodetic Engineering | 628,000,000 | 1,238 | 7 | 12 | 6 | 480 |
| 11 | Geological Engineering | 620,923,400 | 1,247 | 9 | 9 | 32 | 419 |
| 12 | Computer Engineering | 478,500,000 | 1,238 | 7 | 10 | 13 | 558 |

Table 4. Efficiency Output Recapitulation

| DMU | GTE | PTE | SE | Return to Scale |
|---|---|---|---|---|
| Civil Engineering | 0.88 | 1 | 0.88 | Decrease |
| Architecture | 0.67 | 0.74 | 0.90 | Decrease |
| Chemical Engineering | 1 | 1 | 1 | - |
| Urban and Regional Planning | 0.85 | 0.88 | 0.97 | Decrease |
| Mechanical Engineering | 1 | 1 | 1 | - |
| Electrical Engineering | 0.85 | 0.86 | 0.98 | Decrease |
| Marine Engineering | 1 | 1 | 1 | - |
| Industrial Engineering | 1 | 1 | 1 | - |
| Environmental Engineering | 1 | 1 | 1 | - |
| Geodetic Engineering | 0.81 | 1 | 0.81 | Increase |
| Geological Engineering | 1 | 1 | 1 | - |
| Computer Engineering | 1 | 1 | 1 | - |
| Average | 0.92 | 0.96 | 0.96 | - |

Table 5. Slack Recapitulation of Input Variables

| DMU | V1 (IDR million) | V2 ($m^2$) | V3 (People) | V4 (People) |
|---|---|---|---|---|
| Civil Engineering | 0 | 0 | 0 | 0 |
| Architecture | 0 | 1,019 | 0 | 4,185 |
| Chemical Engineering | 0 | 0 | 0 | 0 |
| Urban and Regional Planning | 16,236 | 0 | 0.792 | 10,721 |
| Mechanical Engineering | 0 | 0 | 0 | 0 |
| Electrical Engineering | 72,254 | 0 | 1,741 | 5,619 |
| Marine Engineering | 0 | 0 | 0 | 0 |
| Industrial Engineering | 0 | 0 | 0 | 0 |
| Environmental Engineering | 0 | 0 | 0 | 0 |

| | | | | |
|---|---|---|---|---|
| Geodetic Engineering | 0 | 0 | 0 | 0 |
| Geological Engineering | 0 | 0 | 0 | 0 |
| Computer Engineering | 0 | 0 | 0 | 0 |

In terms of the scope of operations, the five departments were judged to be inefficient. Nonetheless, two of them, Civil Engineering and Geodetic Engineering, had a PTE score of 1 or efficient as a result from the VRS model computation. The other three departments, Architecture, Urban and Regional Planning, and Electrical Engineering, had value result less than 1. This demonstrated that Civil Engineering and Geodetic Engineering had already efficient in terms of resource management, but not on operation scale. On the other hand, Department of Architecture, Urban and Region Planning, and Electrical Engineering had not been efficient both in terms of resource management and operation scale.

Further information about input variables that can be minimized was indicated by the DMU slack value. Slack value was interpreted as variables that could be reduced to improve efficiency. A DMU with a slack greater than 0 was indicated as an inefficient DMU. The unit of slack followed the unit that was used in the efficiency calculation, as shown in Table 5. Input variables with significant values were usage of fund in a year, number of education staffs, and number of lecturers. Slack of building area variables was only appeared on the Architecture Department with value of 1.019 (building area = 4.397 m2) which was relatively small. This could be said that the variable of building area did not have much effect on the efficiency of any department. Meanwhile, the other three variables had fairly large numbers and could be implemented to improve efficiency. Based on the value of slack, reducing input variable could be recommended for the inefficient department. Architecture Department could reduce the lecturer number by 4 or 5 people; Urban and Region Planning could reduce the financial plan by IDR 16.2 million, reduce the number of education staffs by a person, and reduce the number of lecturers by 5 or 6 people; and Electrical Department could. reduce the financial plan by IDR 72.2 million, reduce the number of education staffs by 1 or 2 people, and reduce the number of lecturers by 5 or 6 people. Minimizing these input variables could be accomplished by several ways, for example, reducing the cost of curriculum and practicum implementation, reducing the demand for educational personnel, and not increasing the number of lectures and/or by transferring them to other institutions.

## 4.2 Market Position Mapping

The data used for the dimension of market attractiveness in mapping position market was data on the number of applicants for new student registrants from 2017 to 2020. The number of applicants was limited to new student admission system that carried out independently by each state university (called *Ujian Mandiri* or UM). Meanwhile, the data used for competitive strength dimension was the number of applicants for new student registrants and the number of available capacities in 2020 from three entrance systems at the Faculty of Engineering, which are SNMPTN (new student admission system based on school report cards and non-academic achievement of students during high school), SBMPTN (new student admission system based on tests that are administered simultaneously), and UM. The dimension of market attractiveness was limited to number of applicants in UM admission systems because the implementation system of SNMPTN and SBMPTN could change from year to year so it could not be used as reliable growth assessment. The data on the competitive strength of the study program was limited to a single time period so that it was not influenced by changes in the system for implementing the admission selection.

### 4.2.1 Competitive Strength Dimension

Based on data comparison between the number of new student applicants and the available capacity in each study program, Civil Engineering had the highest competitive strength score, followed by Industrial Engineering, which had a nearly identical score. There was a sharp decline from position 2 to 3. Meanwhile, Architecture, Urban and Regional Planning, Chemical Engineering, Environmental Engineering, Computer Engineering, Mechanical Engineering, Geological Engineering, and Geodetic Engineering ranked third to eleventh, with value close to each other. Being in the last position, Marine Engineering had a value far below than the eleventh rank. The average competitive strength value of the 12 study programs used as the middle limit of matrix was 14.6. There were 5 study programs with values greater than the middle limit, while 7 study programs had competitive strength score lower than the middle limit.

### 4.2.2 Market Attractiveness Dimension

Based on the number of applicants for new student registrants on UM systems from 2017 to 2020, undergraduate program of Computer Engineering was a study program with the highest market attractiveness value followed by Industrial Engineering. The last position was Marine Engineering Department with a negative value of 5.9%, indicating that this undergraduate program had decreased the number of registrants between years. The average market attractiveness value of the 12 study programs used as the middle limit of matrix was 22.2 %. Based on the value of each department, there were 7 study programs had market attractiveness value below the middle limit, while the remaining departments had market attractiveness value above the middle limit.

### 4.2.3 Final Result Mapping

After obtaining the competitive strength and market attractiveness value also middle limit value of both matrixes, all undergraduate program mapped into the market position matrix. First, undergraduate programs that included in star category were Industrial Engineering and Urban and Regional Planning. Both study programs were competitive and predicted to have a high number of prospective students in the future. These two undergraduate programs are very appropriate to allocate resources in order to increase their competitive strength in response to the increasing of market interest. The best strategy for those are to allocate resources and develop the current advantages. Second, undergraduate programs that included in question mark category were Computer Engineering, Environmental Engineering, Electrical Engineering, Mechanical Engineering, and Geodetic Engineering. These five undergraduate programs are considered to have high market attractiveness even though the value of competitive advantages were not optimal. Before allocating resources related to the long-term prospect of the study program, it is necessary to review and reconsider. Third, undergraduate programs that included in cash cow category were Architecture, Civil Engineering, and Chemical Engineering. The three study programs were assessed to have high competitive advantages but with a market attractiveness that had not developed significantly over the years. Increasing the resource allocation was considered not to give high returns because it was no supported by significant market movements. The recommendation for those program study is to maintain their competitive advantage while not requiring a large resource to develop it. Last, undergraduate programs that included in lose category were Geological Engineering and Marine Engineering. These two program studies were stated to have low competitive advantage and market attractiveness relative to others. The allocation of resources given was assumed not to provide balanced results because of its low competitive strength and market interest. The right allocation strategy is to reduce resource allocation and/or minimize expenditure.

The mapping of market positions carried out on 12 undergraduate study programs at Engineering Faculty, Diponegoro University, will be based on existing market interest. To make prospective applicants choose Diponegoro University over other universities for the study program they are interested in, the study programs need to find a way how prospective applicant choose it, for example, increasing student and lecturer achievements, improving and adding facilities, or collaborating with companies in the knowledge field to make study programs more competitive with other universities. (Figure 2)

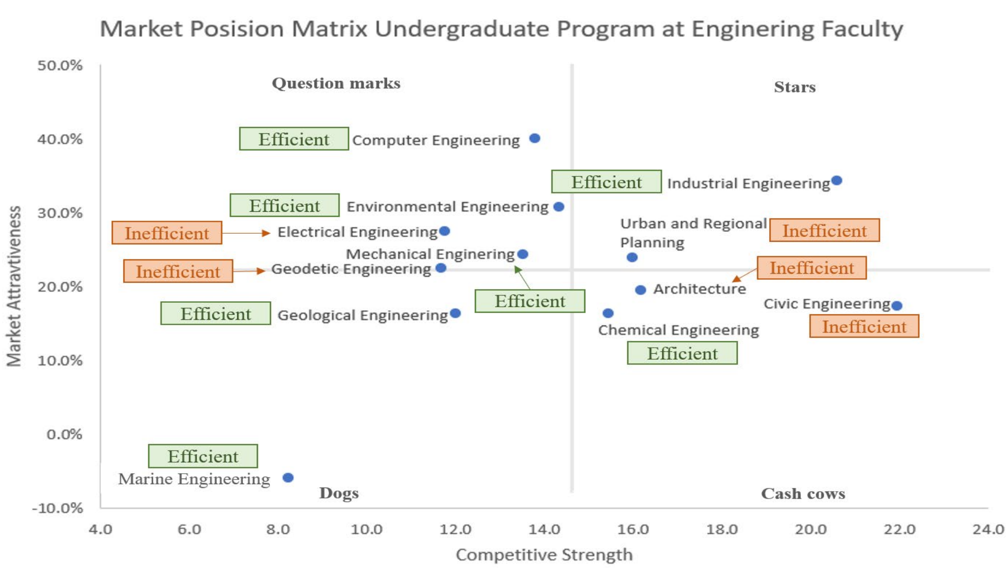


Figure 2. The Combination of Efficiency and Market Position

### 4.2.4 Combination of Efficiency Value and Market Position

The results of the combination between efficiency value and market position of undergraduate program are shown in Figure 2. The focus of this research was to create a resource allocation strategy that the Faculty of Engineering could use to develop study programs and achieve maximum results per resources used. The undergraduate programs in the star and question mark category had a strong market position (with further consideration). Based on the combination, the first option for investing in the development of the study program was Industrial Engineering, which was considered as efficient and in the star category. Industrial Engineering undergraduate programs was expected to be able to make the best use of investment in terms of efficiency, as well as able to develop competitive strength and market attractiveness. The following options were Computer Engineering, Environmental Engineering, and Mechanical Engineering, all of which were considered efficient and were in the question mark category. The three study programs were efficient enough that they were believed to be capable of managing investment as well as possible in order to increase their competitive strength and support high market attractiveness, so that they could one day became stars.

## 5. Conclusion and Recommendation

The strategic of resource allocation is very important in university to be done, particularly state university, with the aim of maximizing the use of resources to achieve optimal results. Two factors that need to be considered when formulating an allocation strategy are the performance and market position of each study program. Based on the combination of both factors, Faculty of Engineering can determine the priority of resource allocation with the best prospects. According to the efficiency calculations performed using DEA method, there are five departments that were considered inefficient, which were Civil Engineering, Architecture, Urban and Regional Planning, Electrical Engineering and Geodetic Engineering. The recommendations were to reduce the scale of operations for the five study programs to the optimal size and to improve the efficiency of resource management for Departments of Architecture Urban and Regional Planning, and Electrical Engineering. In terms of market position, the study programs categorized as star were Industrial Engineering and Urban and Region Planning. The study programs categorized as question mark were Computer Engineering, Environmental Engineering, Electrical Engineering, Mechanical Engineering, and Geodetic Engineering. The study programs categorized as cash cows were Architecture, Civil Engineering, and Chemical Engineering. The remaining study programs, Geological Engineering and Marine Engineering, were in lose category. The first choice to invest the development of the study program was Industrial Engineering which was considered efficient and in the star category. The following options were Computer Engineering, Environmental Engineering, and Mechanical Engineering, all of which were considered efficient and were in the question mark category, which were efficient enough that they were believed to be capable of managing investment as well as possible to increase their competitive strength and support high market attractiveness, so that they could one day became stars.

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