



THE ECONOMIC ESSENCE AND TYPES OF INDUSTRIAL ENTERPRISE EFFICIENCY AND THE EVOLUTION OF APPROACHES TO ITS ASSESSMENT

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Abstract: The article clarifies the economic content of the category of industrial enterprise efficiency, systematizes its types and analyzes the historical development of assessment methods. The concepts of productivity, efficiency and effectiveness are distinguished, and the theoretical legacy of M. Farrell, H. Leibenstein and R. Solow is comparatively assessed. Technical, allocative, economic, scale, dynamic, organizational and equipment efficiency are described together with their theoretical foundations and their manifestation in railway industrial enterprises. Assessment methods are divided into ratio-based, parametric, non-parametric frontier and integrated data-driven stages. It is substantiated that the types of efficiency are arranged hierarchically rather than in parallel, that data requirements increase with each new stage of assessment, and that data are becoming a resource that determines the capacity to manage efficiency.

Keywords: efficiency, productivity, industrial enterprise, technical efficiency, X-efficiency, data envelopment analysis, stochastic frontier analysis, Malmquist index, railway industrial enterprises.



Introduction

When a company manager asks, “Is our plant operating efficiently?”, he or she actually has one of three different questions in mind: how much output is there per worker or per sum of fixed assets; how much more output does a competing enterprise produce with exactly the same resources; and has the enterprise fulfilled its plan? In everyday speech, the concepts that answer these questions are often used interchangeably, but in scientific analysis this confusion leads to serious errors.

The problem is particularly relevant for railway industrial enterprises: internal transfer prices dominate in them, while the reporting practice of Uzbek enterprises is still dominated by analysis based on individual ratios.

The scientific problem is that, in multi-product and multi-resource production, the question of who sets the weights that reduce outputs and resources to a single indicator, and how, remains open.

The purpose of the article is to clarify the economic content of the category of industrial enterprise efficiency, to systematize its types and to analyze the evolution of assessment approaches, thereby substantiating the following thesis: the most accurate way to measure the efficiency of an industrial enterprise is to determine its distance to the empirical “best-practice frontier”, which also includes its data (information) resource, while assessment methods have historically evolved from individual ratios to frontier methods and from these to data-driven hybrid models.

Literature Review

In the economic literature, the three questions above are answered, respectively, by the concepts of productivity, efficiency and effectiveness (performance). Productivity is the ratio of output to input and is expressed as an absolute magnitude, for example, annual output per employee or value added per hour of labor. F. Bertani, M. Raberto and A. Teglio define labor



productivity as a measure of how efficiently labor is used in production, and capital productivity as the ratio of gross output to capital services. They define total factor productivity as the residual growth not explained by changes in labor and capital, reflecting how efficiently labor and capital are used together [1]. The authors prefer to measure labor input in hours worked rather than headcount, since a headcount does not distinguish between full-time and part-time employment [1]. In our assessment, this detail matters not only for macro-statistics but also for enterprise analysis: the same number of employees in a car-repair shop working two shifts versus one shift represents different labor input.

Efficiency, by contrast, is a relative and normative concept. It compares an enterprise's actual productivity with the highest productivity attainable under the given technology and resources. Hence, measuring efficiency requires deciding in advance how the "highest attainable level" is to be determined. It is precisely this issue that lies at the center of all theoretical and methodological debates on efficiency. Effectiveness, in turn, characterizes the degree to which an enterprise achieves its goals and may not directly take resource use into account: even if a plan is 100 percent fulfilled, it may well have been achieved at excessive cost.

The practical consequence of this distinction is clearly shown by the study of S. Mishra, M. Ewing and H. Cooper. They distinguish gross operational efficiency as sales per employee and net operational efficiency as net profit per employee [2]. Based on 15 years of 10-K reports of 4,052 firms listed in the USA, they found that a focus on artificial intelligence is negatively associated with gross operational efficiency and positively associated with net operational efficiency. The authors explain this by costs growing more slowly than revenue [2]. This result is methodologically valuable: the same technology in the same enterprise appears to reduce efficiency by one indicator and increase it by another. The approach of Mishra and co-authors is not without



weaknesses: “AI focus” is measured by the frequency of keywords in reports and reflects the announcement of the technology rather than its actual application. Nevertheless, the idea of separating gross and net efficiency is directly transferable to railway industrial enterprises.

Why should an enterprise’s efficiency be compared with real competitors rather than with a theoretical ideal? The first systematic answer to this question was given by M. Farrell in 1957. His article proposed basing the measure of efficiency on the best observed results rather than on a theoretical form of a “fully efficient” production function [3]. Farrell divided overall efficiency into two parts. Technical efficiency refers to the ability to obtain maximum output from given resources. Price (allocative) efficiency is the ability to use resources in optimal proportions, taking their prices into account [3]. The author tested his approach on agricultural data from 48 US states and thereby demonstrated that the frontier idea is practical.

The strength of Farrell’s approach is its empiricism. An enterprise is compared not with an abstract engineering standard but with the “envelope” formed by the best-performing enterprises under the same conditions. The distance from this frontier serves as the measure of inefficiency. In our assessment, the limitation of this approach is hidden here as well: the frontier is constructed only at the level of the enterprises in the sample, and if all enterprises in the industry are at a low technological level, the best of them is declared “fully efficient”. In other words, Farrell’s frontier measures relative efficiency, not absolute potential.

Nine years after Farrell, H. Leibenstein looked at the efficiency problem from a completely different angle. Introducing the concept of “X-efficiency”, he argued that enterprises operate below their potential frontier not only because of technology or prices but also because of internal organizational factors [4]. According to Leibenstein, employment contracts are incomplete, the level of employee effort is not precisely specified, and the production



function is not fully known. As a result, enterprises with the same resources produce different results. His evidence was that empirical estimates of the allocative losses caused by monopoly turned out to be very small, while productivity differences between enterprises were much larger [4]. Leibenstein's most important conclusion concerns competitive pressure: in an environment with low pressure, X-inefficiency is high.

If we compare the views of Farrell and Leibenstein, the contradiction between them becomes apparent. For Farrell, inefficiency is a measurable distance, while its cause remains outside the model. For Leibenstein, the cause is what matters: motivation, information and control. However, Leibenstein did not propose a specific method for quantifying X-inefficiency. In our view, these two approaches are not mutually exclusive but rather complementary. Farrell's frontier answers the question "how much?", while Leibenstein's theory answers the question "why?".

The third theoretical pillar is the work of R. Solow. In 1957, using an aggregate production function, he isolated the part of growth not explained by capital and labor. According to Solow's calculations, gross output per worker-hour in the USA doubled between 1909 and 1949, with 87.5 percent of this growth attributable to technical change and the remaining 12.5 percent to increased use of capital [5]. The advantage of the Solow residual is that it provided a transparent and replicable method of measuring technological progress. Its drawback is that the residual is a "measure of our ignorance": it absorbs technology, management quality and measurement errors alike. Solow's model assumes that all enterprises operate on the frontier, that is, it does not recognize the inefficiency pointed out by Farrell and Leibenstein.

Authors are not unanimous on the classification of efficiency types either. Farrell's classical scheme has only two types. Leibenstein adds an organizational dimension to this scheme and considers it more important than allocative efficiency. R. Färe and co-authors shift the focus from the static state



to dynamics and decompose productivity growth into efficiency change and technical progress [6]. For S. Nakajima, efficiency is not an economic category at all but an engineering indicator at the equipment level [7].

Research Methodology

The information base of the study consisted of classical and contemporary scientific publications and empirical studies on efficiency theory and methods of its measurement. Categorical analysis was used to distinguish the concepts of productivity, efficiency and effectiveness by their measurement properties. Comparative analysis identified the strengths and weaknesses of the authors' views and the contradictions between them; in particular, the positions of Farrell and Leibenstein and of Andersen–Petersen and Banker–Chang, as well as the SFA and DEA methods, were compared. Using the systematization method, efficiency types and assessment approaches were summarized in tables. Based on the historical-logical approach, the development of assessment methods was divided into four stages, with each stage regarded as a response to a specific limitation of the previous one. In the formula-based analysis, the general weighted ratio of efficiency, its decomposition into technical, allocative, pure technical and scale components, the Cobb–Douglas function, the SFA and CCR models, the Malmquist index and the OEE indicator were examined, and the meaning of each for managerial decision-making was explained using the examples of car-repair, foundry and machining production.

Analysis and Results

The general expression of efficiency and the problem of weights. In its simplest and most general form, efficiency is written as the weighted ratio of the sum of outputs to the sum of inputs:

$$E = \frac{\sum_{r=1}^s u_r y_r}{\sum_{i=1}^m v_i x_i}, \quad (1)$$



where y_r is the enterprise's output of type r (number of cars produced, units repaired, revenue), x_i is the consumption of resource of type i , u_r and v_i are the weight coefficients of outputs and resources, and s and m are the numbers of output and resource types. With a single product and a single resource, formula (1) becomes a simple productivity indicator. In multi-product and multi-resource production, however, the question of who sets the weights and how remains open. If the weights are given by prices, the indicator becomes tied to the price structure. This is dangerous for the railway system, where internal transfer prices dominate. If the weights are chosen by experts, the assessment becomes subjective. We believe that the subsequent seventy years of development of efficiency theory have been aimed precisely at solving this problem of weights.

Components of efficiency. In Farrell's model, the relationship between technical and price efficiency is expressed as a product [3]:

$$EE = TE \times AE, \quad (2)$$

where EE is economic (cost) efficiency, i.e. the ratio of the minimum possible cost to the actual cost, TE is technical efficiency, and AE is allocative efficiency. All three quantities lie in the range from 0 to 1. The managerial meaning of formula (2) is clear: if an enterprise's economic efficiency is 0.6, the analyst can determine what part of this loss stems from technological lag and what part from imbalance in the resource mix.

Since Farrell's frontier is relative, it is not enough to compare Uzbekistan's railway industrial enterprises only with one another; they must also be compared with foreign railway companies and other industrial sectors. Leibenstein's conclusion is especially relevant for enterprises within the system of JSC "O'zbekiston temir yo'llari" (Uzbekistan Railways), which are dominated by state ownership and work for an internal customer, since most of their output is sold within the system rather than in a competitive market. Artificial intelligence technologies are aimed directly at reducing precisely



those sources of X-inefficiency that are associated with information asymmetry, delayed decisions and weak control.

At the enterprise level, Solow's idea is written using the Cobb–Douglas function:

$$Y_t = A_t K_t^\alpha L_t^\beta M_t^\gamma \Rightarrow \ln A_t = \ln Y_t - \alpha \ln K_t - \beta \ln L_t - \gamma \ln M_t, \quad (3)$$

where Y_t is the enterprise's output in period t , A_t is total factor productivity, K_t , L_t and M_t are capital, labor and material resources, and α , β , γ are their elasticity coefficients. Bertani and co-authors model the impact of digital assets precisely through this A_t : in their model, firms operate with a Cobb–Douglas function with constant returns to scale, and digital asset innovation is introduced as a factor that raises total factor productivity [1].

Placing the views of Farrell, Leibenstein and Solow side by side leads, in our opinion, to one conclusion: modern efficiency analysis must simultaneously capture the shift of the frontier (Solow), the distance from the frontier (Farrell) and the organizational causes of this distance (Leibenstein).

Types of efficiency and their interrelationship. For a comprehensive assessment of an industrial enterprise, it is advisable to distinguish at least seven types. Their systematized description is given in Table 1.

Table 1

Types of industrial enterprise efficiency, their content and manifestation in railway industrial enterprises

Type	Economic content	Measurement indicator	Manifestation in a railway industrial enterprise	Theoretic al basis
Technical	Obtaining maximum output	DEA score 0–1, equipment utilization rate	Number of cars repaired per shift	Farrell, 1957



Type	Economic content	Measurement indicator	Manifestation in a railway industrial enterprise	Theoretic al basis
	from given resources			
Allocat ive	Using resources in optimal proportions consistent with their prices	Factor price ratio, cost structure	Balance between spare-parts inventory and labor costs	Farrell, 1957
Econo mic (cost)	Product of technical and allocative efficiency	Ratio of minimum cost to actual cost	Cost of repairing one car	Farrell, 1957
Scale	Correspondence of output volume to the optimal level	Ratio of CCR and BCC scores	Plant capacity utilization rate	Banker, Charnes, Cooper, 1984
Dynam ic	Shift of the frontier and catching up with it	Malmquist index, total factor productivity	Change in productivity over the years	Solow, 1957; Färe et al., 1994
Organi zationa l (X)	Quality of management, incentives and information	Downtime, decision-making time	Working time lost due to downtime	Leibenstein, 1966



Type	Economic content	Measurement indicator	Manifestation in a railway industrial enterprise	Theoretic al basis
Equip ment (operat ional)	Equipment losses in availability, speed and quality	OEE	Load of foundry and machining lines	Nakajima, 1988

Source: compiled by the author based on the works of Farrell, Leibenstein, Banker and co-authors, Färe and co-authors, and Nakajima [3, 4, 6, 7, 8].

Table 1 shows that the types of efficiency are arranged hierarchically rather than in parallel. Economic efficiency breaks down into technical and allocative types, and technical efficiency, in turn, into pure technical and scale efficiency. The last column of the table shows that each type has its own theoretical school. This confirms our thesis that no single indicator can capture all types.

The decomposition of technical efficiency into its components was substantiated by R. Banker, A. Charnes and W. Cooper in 1984 through the development of the variable returns to scale model [8]:

$$TE_{CCR} = PTE_{BCC} \times SE, \quad (4)$$

where TE_{CCR} is overall technical efficiency under the assumption of constant returns to scale, PTE_{BCC} is pure technical efficiency under the assumption of variable returns to scale, and SE is scale efficiency. This decomposition is of decisive importance for managerial decisions. If an enterprise's inefficiency is mainly explained by low PTE , the reserve lies in management, technology and work organization. In this case, AI-based planning and diagnostics deliver a direct effect. If inefficiency is explained by low SE , the problem lies in the mismatch between capacity and the order



portfolio. Here no algorithm will eliminate a shortage of orders; the production program needs to be revised.

Our position regarding the contradiction between classifications is that these views belong to different levels of management. Nakajima's indicator works at the shop and line level, Farrell's and Banker's indicators at the enterprise level, and Färe's index at the industry level and over time. Therefore, they should not be set against one another but linked by level.

Financial efficiency (return on assets and equity) was deliberately not included in the table as a separate type. There is a reason for this. In an enterprise operating with internal transfer prices, profitability is largely the result of pricing policy and does not accurately reflect the quality of resource use. We regard financial indicators not as an independent type of efficiency but as its external expression.

The evolution of assessment approaches. Methods of measuring efficiency have developed through four stages. Each stage emerged as a response to a specific limitation of the previous one. This sequence is summarized in Figure 1.

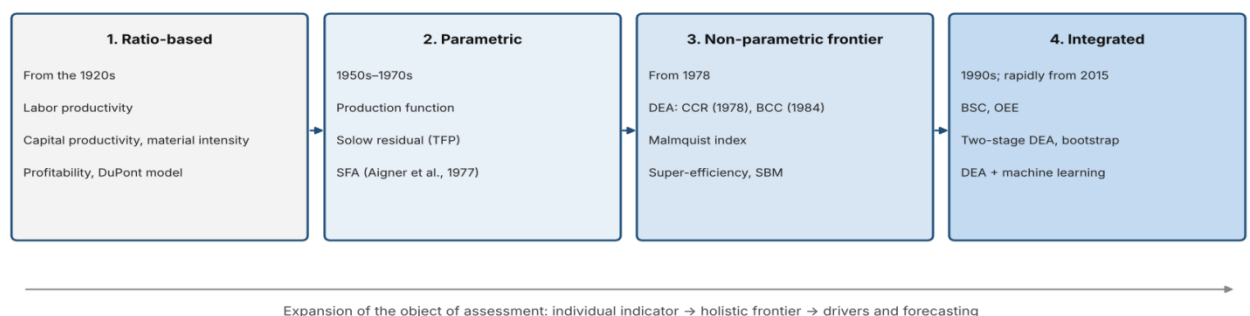


Figure 1. Evolution of approaches to assessing industrial enterprise efficiency

Source: developed by the author based on the works of Farrell, Aigner and co-authors, Charnes and co-authors, and Simar and Wilson [3, 9, 10, 11].

Figure 1 reflects the consistent expansion of the object of assessment: from an individual indicator to a holistic frontier, and from there to efficiency



drivers and forecasting. Each subsequent stage does not cancel the previous one but encompasses it. The fourth stage in the figure treats data both as an analytical tool and as a resource, which confirms the second part of the article's thesis.

The first stage is the ratio-based approach, which became widespread from the 1920s. Enterprise efficiency was assessed through labor productivity, capital productivity, material intensity and profitability. The DuPont model, which decomposes profitability into net profit margin, asset turnover and financial leverage, is the classic form of this approach. In the economic school of the former Soviet Union, it developed under the name "analysis of economic activity" and still dominates the reporting practice of Uzbek enterprises. The advantage of the approach is its simplicity and reliance on accounting statements. Its drawback, however, is serious: individual indicators often give contradictory signals. The result of Mishra and co-authors illustrates this: sales per employee decreased, while net profit per employee increased [2]. In such a case, a system of ratios cannot tell which signal prevails.

The second stage is the parametric, i.e. econometric, approach. While statistical estimation of the production function began with Solow's work, the direct incorporation of enterprise inefficiency into the function was carried out by D. Aigner, K. Lovell and P. Schmidt in 1977. They proposed Stochastic Frontier Analysis (SFA), in which the error term is split into two components [9]:

$$\ln y_i = f(x_i, \beta) + v_i - u_i, \quad v_i \sim N(0, \sigma_v^2), \quad u_i \geq 0, \quad (5)$$

where y_i is the output of enterprise i , $f(x_i, \beta)$ is the frontier function defined by the resource vector x_i and parameters β , v_i is normally distributed random noise, and u_i is the non-negative inefficiency term. Aigner and co-authors used a half-normal distribution for u_i [9]. The main achievement of SFA is that it separates deviations caused by weather, unexpected equipment breakdowns or measurement error from inefficiency. The price, however, is



two strict assumptions: the functional form (Cobb–Douglas or translog) and the distribution of u_i must be chosen in advance. In our assessment, in an industry with few observations, for example a railway industrial complex consisting of several dozen enterprises, these assumptions largely predetermine the result.

The third stage is the non-parametric frontier approach. In 1978, A. Charnes, W. Cooper and E. Rhodes proposed Data Envelopment Analysis (DEA), generalizing Farrell's idea to the multi-input, multi-output case [10]. They introduced the concept of the Decision Making Unit (DMU) and elegantly solved the weights problem in formula (1): the weights are not set externally but are chosen through linear programming for each unit so as to present it in the most favorable light. The input-oriented CCR model under constant returns to scale is written as follows:

$$\min_{\theta, \lambda} \theta \quad \text{s.t.} \quad \sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{io}, \quad \sum_{j=1}^n \lambda_j y_{rj} \geq y_{ro}, \quad \lambda_j \geq 0, \quad (6)$$

where θ is the technical efficiency of the evaluated enterprise o , x_{ij} and y_{rj} are resource j and output i of enterprise r , λ_j are the weights of the benchmark enterprises, and n is the number of enterprises. By adding the constraint $\sum_j \lambda_j = 1$ to the model, Banker, Charnes and Cooper created the variable returns to scale (BCC) model [8]. It is these two models that make it possible to calculate decomposition (4).

The transition from static assessments to dynamics was made through the Malmquist index. Färe, Grosskopf, Norris and Zhang decomposed it, on the basis of distance functions, into efficiency change and technical change and applied it to data from 17 OECD countries for 1979–1988 [6]:

$$M_{t,t+1} = \underbrace{\frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)}}_{\check{EC}} \times \underbrace{\left[\frac{D^t(x_{t+1}, y_{t+1})}{D^{t+1}(x_{t+1}, y_{t+1})} \cdot \frac{D^t(x_t, y_t)}{D^{t+1}(x_t, y_t)} \right]^{1/2}}_{\check{TC}}, \quad (7)$$



where D^t is the distance function relative to the technology of period t , EC is the enterprise's catching up with the frontier (efficiency change), and TC is the shift of the frontier itself (technical change). If the index is greater than one, productivity is considered to have grown. In our view, formula (7) is the most suitable tool for studying the impact of artificial intelligence: if a technology is adopted by several enterprises in an industry, it first changes TC , and then, as laggards catch up, EC .

The internal limitations of DEA were also soon identified. First, several enterprises turn out to be equally efficient at once, and they cannot be ranked. As a solution, P. Andersen and N. Petersen proposed the super-efficiency procedure: the evaluated unit is excluded from the reference set, so that its score can exceed one [12]. In 2006, R. Banker and H. Chang showed that this procedure is suitable not for ranking but for identifying outliers [13]. The debate between these two positions is, in our view, resolved in favor of Banker and Chang, since the super-efficiency score is in many cases sensitive to a single unusual observation. The second limitation is that the DEA score is deterministic and does not separate random noise from inefficiency. In this respect, SFA and DEA are mirror images of each other: one separates noise but requires a functional form, while the other requires no functional form but is sensitive to noise.

The fourth stage is the integrated, data-driven approach. One of its directions descends to the equipment level. Within the Total Productive Maintenance (TPM) concept, Nakajima proposed the Overall Equipment Effectiveness indicator [7]:

$$OEE = A \times P \times Q, \quad (8)$$

where A is the availability rate (the share of planned working time without downtime), P is the performance rate (the ratio of actual speed to rated speed), and Q is the quality rate (the share of good products in total output). Nakajima divides equipment losses into six major loss groups and measures



them through three rates [7]. This indicator is particularly convenient for repair and foundry production, as it directly converts downtime and defects into efficiency losses.

The second direction is related to enriching frontier methods with statistical inference. In the two-stage analysis widely used in practice, DEA scores are calculated in the first stage, and in the second stage they are related to external factors through regression. L. Simar and P. Wilson showed that statistical inference in such conventional two-stage analysis is invalid because DEA scores are serially correlated and biased in an unknown way. They proposed a consistent algorithm based on truncated regression and a bootstrap procedure [11]. In our assessment, this work is a bridge between the third and fourth stages: the efficiency score is no longer the final result but becomes the dependent variable for further analysis.

The third direction is the use of machine learning methods. The random forest algorithm proposed by L. Breiman combines a large number of decision trees and identifies non-linear relationships without specifying a functional form in advance [14]. Gradient boosting, developed by J. Friedman, improves prediction accuracy through a chain of models that successively correct errors [15]. When combined with DEA, these methods perform two tasks: they rank efficiency drivers and forecast efficiency for future periods. In this way, assessment turns from a retrospective calculation into a prospective management tool. A comparative description of the four stages is given in Table 2.



Table 2

Comparative description of approaches to efficiency assessment

Approach	Period	Main methods	Advantages	Limitations	Data requirements
Ratio-based	From the 1920s	Productivity, capital productivity, profitability, DuPont model	Simple, relies on financial statements	Does not give a holistic assessment, indicators conflict	Low, accounting statements
Parametric	1957–1977	Production function, Solow residual, SFA	Separates noise, statistical testing possible	Functional form and distribution chosen in advance	Medium, large sample needed
Non-parametric frontier	From 1978	DEA (CCR, BCC), Malmquist index, super-efficiency	Multiple inputs and outputs, no weights required	Sensitive to noise, does not forecast	Medium, physical and value indicators
Integrated, data-driven	From 1988, rapidly from 2015	OEE, two-stage DEA with bootstrap, hybrid DEA and machine learning	Identifies drivers, forecasts	Depends on data quality and volume	High, sensor and information system data



Source: compiled by the author based on the works of Charnes, Cooper and Rhodes, Aigner and co-authors, and Simar and Wilson [9, 10, 11].

The last column of Table 2 reveals an important pattern: with each new stage, the data requirements of assessment increase. An annual report is sufficient for ratio analysis, whereas hybrid models require a continuous flow from sensors and corporate information systems. Consequently, beyond being a prerequisite for the assessment method, data become a resource that determines the capacity to manage efficiency.

Conclusions and Recommendations

Productivity, efficiency and effectiveness are independent concepts that answer different questions, and efficiency is most accurately measured as an enterprise's distance to the empirical "best-practice frontier". The approaches of Farrell, Leibenstein and Solow complement one another by measuring the distance from the frontier, its organizational causes and the shift of the frontier. The seven types of efficiency are arranged hierarchically and belong to different levels of management, so they cannot be captured by a single indicator. Assessment methods have evolved from ratios to frontier methods and from these to data-driven hybrid models, and data themselves have become a resource for managing efficiency.

Based on the results, the following recommendations have been developed:

1. In railway industrial enterprises, measure labor input in hours worked and calculate gross and net operational efficiency separately.
2. Under internal transfer pricing, use profitability as an external expression of efficiency and rely on the DEA method, which determines weights through linear programming.
3. Before choosing measures, decompose technical efficiency into pure technical and scale components: with low pure technical efficiency, prioritize



management, technology and work organization; with low scale efficiency, prioritize revision of the production program.

4. Apply the OEE indicator at the shop and line level, DEA scores at the enterprise level, and the Malmquist index at the industry level and over time, and use the super-efficiency procedure only to identify outliers.

5. Analyze efficiency drivers using a consistent bootstrap-based algorithm and develop the data infrastructure of sensors and corporate information systems as a resource for managing efficiency.

In further research, it is advisable to compare the efficiency of Uzbekistan's railway industrial enterprises with foreign railway companies and other industrial sectors, and to analyze in detail the channels through which artificial intelligence technologies reduce sources of X-inefficiency.

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