QUANTITATIVE FORECASTING APPROACH TO IDENTIFY WORKFORCE GAPS IN ENERGY SECTOR

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Abstract. The energy sector in Latvia is widely recognized as a cornerstone of sustainable economic development, with increasing emphasis on technological advancement, digitalization, and innovation. Despite this focus, limited attention has been paid in the academic literature to internal alignment challenges within the sector, particularly the mismatch between human resource capacity and the rapidly evolving engineering and technological requirements. This study analyses data obtained during the first stage of a broader research framework, focusing on the application of adaptive forecasting approaches in human resource development and planning within the energy sector. The methodological approach is based on quantitative analysis of workforce data, applying adaptive forecasting principles to assess human resource demand under dynamic technological and operational conditions. The results of the research indicate that workforce qualification and responsibility data are limiting effective human resource planning. The findings show that workforce capacity modelling demonstrates the applicability of adaptive forecasting approaches for analysing workforce demand under dynamic operational conditions, highlighting their potential to support more coherent and responsive workforce planning. These initial results provide a critical foundation for the subsequent stages of the research, which will further explore integrated forecasting tools and policy recommendations for workforce development in the Latvian energy sector.

Keywords: adaptive forecasting, human resource planning, workforce structural alignment, energy sector, skills mismatch

Introduction

The energy sector is undergoing structural transformation driven by decarbonisation targets, technological advancement, and digitalisation. The transition toward low-carbon energy systems reshapes employment structures, occupational compositions, and regional workforce distributions [1-2]. Renewable generation, storage, and grid modernisation require new competency profiles and revised workforce planning approaches, while geographical mismatches between emerging energy jobs and existing skill bases further complicate labour market adaptation [1; 3]. These developments increase the need for adaptive and data-driven human resource planning in energy-intensive sectors.

At the European Union level, the energy sector (NACE Section D – electricity, gas, steam and air conditioning supply) employed approximately 1.42 million in 2023, representing around 0.73 % of total employment. According to Eurostat, this relatively low employment share reflects the capital-intensive and technologically advanced nature of the sector, which generates high economic value despite employing a limited proportion of the workforce [4]. In Latvia, during the same period, the energy sector (NACE Section D) employed 9.5 thousand persons in 2023, accounting for approximately 1.15 % of total employment. Compared to the EU average, the sector holds a relatively higher share in Latvia's labour market, although the absolute number of employees remains significantly lower, reflecting the smaller scale of the national economy [5].

Table 1

Comparative Employment Indicators in the Energy Sector: EU vs Latvia (2023)

Indicator	European Union	Latvia
Employment (persons)	1 425 649	9 526
Share of total employment	0.73%	1.15%

Source: Eurostat (n.d.) Sector - NACE D – Electricity, gas, steam, air conditioning supply [4; 5]

Beyond macro-level trends, research highlights structural skills imbalance within organisations. Heterogeneous labour structures and uneven skill distribution reduce productivity and distort factor allocation efficiency [6], while qualification mismatches persist even in technologically advanced engineering sectors [7]. Regionally differentiated exposure to the low-carbon transition further reveals uneven vulnerability across occupational groups, emphasising the need for systematic workforce reconfiguration [8]. At the same time, European labour market data indicate growing demand for highly qualified technical specialists. More than 7 million people were employed as researchers and engineers in the EU in 2022, representing approximately 4 % of total employment [9]. However, the supply of STEM graduates remains insufficient, with an average of 14.3 graduates per 1,000 young people aged 20-34 [10].

The importance of engineering-related professions is particularly evident in the energy sector. Electro-engineering workers account for approximately 1.6 % of total EU employment and around 13 % of employment in the electricity, gas, steam and air-conditioning supply sector, underlining the sector's dependence on specialised technical competencies [9]. Taken together, these indicators demonstrate that workforce challenges in the energy sector are closely linked to broader structural shortages in STEM-related occupations. Digital transformation further increases workforce complexity by reshaping task structures, automation levels, and required competencies [11]. Technological change increases demand for adaptive capabilities while reducing tolerance for rigid workforce configurations [12], reinforcing the growing integration between digitalisation and strategic HR practices [13].

Workforce planning and competence alignment are important across all sectors, as global uncertainty, demographic change, and migration increasingly affect labour availability and the balance between workforce supply and sector-specific demand; in OECD countries, permanent-type migration reached a record 6.5 million new immigrants in 2023, highlighting the growing role of migration in addressing labour shortages, while also increasing the complexity of workforce capacity planning [14]. From a strategic perspective, organisational performance under dynamic conditions depends on alignment between HR systems, workforce flexibility, and business strategy. Smart HRM 4.0 practices enhance dynamic capabilities and organisational performance through integrated learning and reconfiguration mechanisms [15], while workforce differentiation and HR flexibility significantly influence firm-level outcomes when aligned with strategic objectives [16]. However, existing research rarely integrates these dimensions into a unified adaptive forecasting framework at the organisational level, particularly in contexts characterised by structural STEM supply constraints. This study does not aim to optimise forecasting accuracy, but rather to assess the feasibility of applying forecasting approaches given the availability and structure of workforce data.

Materials and methods

This study is based on empirical workforce data collected in the Latvian energy sector, comprising organisational records on employee qualifications, job roles, and operational workload indicators. The dataset includes information on formal education levels, technical specialisations, certification categories, task allocation patterns, and responsibility distribution across organisational units. Operational workload is represented through recorded working hours, maintenance cycles, task frequency, and shift intensity indicators.

The analytical focus is placed on modelling workforce demand using operational workload as a proxy for labour requirements. The methodological approach combines structural workforce alignment principles with time-series forecasting techniques. From a theoretical perspective, workforce configuration is interpreted as a structural capability arrangement rather than a purely quantitative headcount, reflecting established findings that labour heterogeneity and uneven skill distribution affect productivity and operational efficiency [6; 7]. This perspective is consistent with strategic human resource alignment theory, which emphasises the role of workforce structure in organisational adaptability [15; 16].

Workforce demand is modelled using time-series forecasting techniques (See Fig. 1.). The SARIMA model is used as the primary forecasting approach due to its ability to incorporate periodic fluctuations associated with maintenance cycles and scheduling structures. This modelling approach aligns with recent developments in workforce demand forecasting that employ data-driven and hybrid modelling techniques [17-20]. To account for uncertainty in projected workforce demand, a Monte Carlo simulation framework is implemented based on the residual variance of the fitted time-series models. Stochastic demand trajectories are generated by introducing random disturbances consistent with model residuals, allowing the estimation of variability ranges and confidence intervals for forecasted workload. In addition to parametric time-series models, Gaussian Process Regression (GPR) is applied as a non-parametric benchmark model to evaluate the robustness of forecasting results across different modelling paradigms. This enables comparative assessment of model behaviour under varying data conditions.

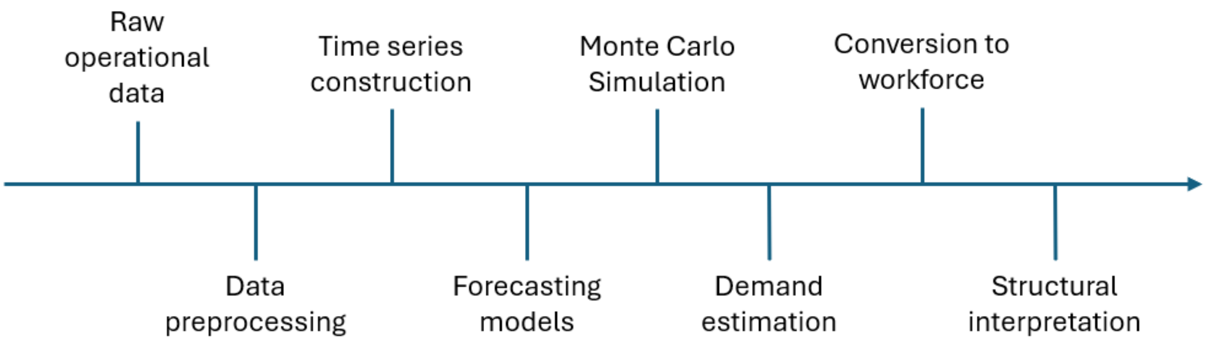

Fig. 1. **Methodological Framework for Workforce Demand Forecasting**

The resulting demand estimates provide a basis for analysing structural imbalances between workforce capacity and operational requirements. Such imbalances are particularly relevant in the context of the energy transition, where occupational restructuring and regional labour exposure create uneven vulnerability across workforce segments [1; 8].

In interpreting the results, broader labour market conditions are considered as contextual factors. Latvian labour-market forecasts identify STEM higher education as a deficit area and emphasise the need to expand admissions and graduations while reducing dropout [21]. EU monitoring similarly indicates that Latvia's STEM graduate output remains below the EU average [22]. These conditions provide relevant context for understanding workforce planning challenges in the energy sector.

Results and discussion

The empirical analysis is interpreted within the broader context of structural labour market developments in the European Union. Employment of researchers and engineers has exceeded 7 million across the EU, while demand for technical specialists continues to grow due to digitalisation and the energy transition [9]. At the same time, the supply of STEM graduates remains insufficient, with approximately 14.3 graduates per 1 000 young people aged 20–34, indicating a structural imbalance between labour demand and supply. Within this context, Latvia represents a more constrained case. STEM graduates account for 19.3 % of all tertiary graduates compared to the EU average of 25.2 %, while the number of STEM graduates per 1,000 population aged 20–29 is 14.7 versus 23.0 in the EU [10].

Table 2

STEM indicators in Latvia and EU based on European Commission (2025)

Indicator (tertiary education)	Latvia	EU average
STEM graduates as a share of all tertiary graduates (2023)	19.3%	25.2%
Women as a share of STEM graduates (2023)	33.7%	33.5%
STEM graduates per 1,000 population aged 20–29 (2023)	14.7	23.0

Source: European Commission. (2025). Education and training monitor 2025 [10]

These constraints are particularly relevant for the energy sector, where specialised technical professions constitute a significant share of the workforce. Electrical engineering specialists alone represent approximately 13 % of employment within the electricity, gas, steam and air-conditioning supply sector, highlighting the strong dependency of energy infrastructure on highly specialised technical labour [9]. These European and national-level trends indicate that workforce challenges in the energy sector are not only organisational but are structurally embedded within broader labour market conditions. Against this background, the empirical analysis of the examined organisation provides insight into how these structural constraints materialise at the enterprise level. The results indicate that workforce planning challenges are primarily structural rather than purely quantitative. Although the total headcount appears numerically sufficient under static evaluation, adaptive modelling reveals pronounced imbalances between qualification profiles and operational demand. Forecasted workload projections, supported by empirical model evaluation, indicate increasing variability in task intensity, particularly in technical maintenance and system monitoring functions. Adaptive time-series modelling captures seasonal peaks and operational fluctuations that are not visible under conventional average-based planning approaches.

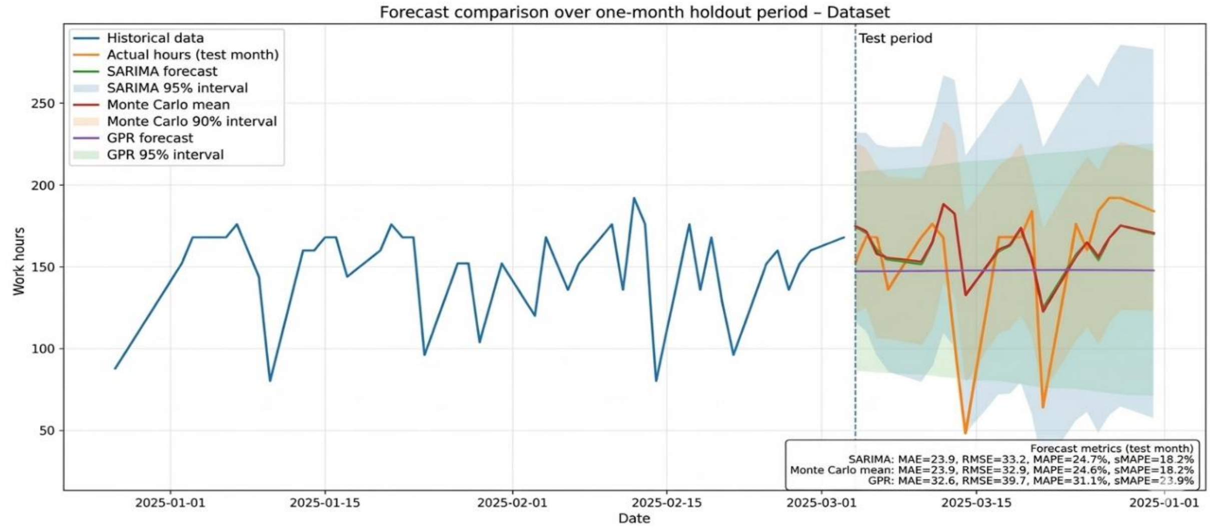

Fig. 2. **Forecast comparison over a one-month holdout period for a selected organisational unit**

The forecasting results further demonstrate demand variability and model sensitivity. As shown in Figure 2, SARIMA captures the primary temporal structure of workload demand (MAPE 24.7 %), while the Monte Carlo extension provides comparable accuracy (MAPE 24.6 %) by incorporating stochastic variation. In contrast, GPR shows lower predictive accuracy (MAPE 31.1 %), suggesting weaker performance in capturing structured seasonality. Beyond accuracy, the results highlight uncertainty dynamics. The Monte Carlo simulation reveals a widening uncertainty range during peak periods, indicating increased volatility and reduced predictability of workload intensity. This suggests that demand fluctuations are amplified under specific operational conditions, with direct implications for workforce allocation. These findings support previous research demonstrating the advantages of dynamic, data-driven forecasting over static allocation approaches [17-19]. In this context, forecasting serves both predictive and diagnostic functions, enabling identification of structurally sensitive demand segments.

Comparison of forecasted demand with workforce capacity reveals structural gaps. In several technical domains, projected demand exceeds available certified personnel during peak periods, creating concentrated overload. At the same time, some qualification categories remain underutilised, indicating internal allocation inefficiencies rather than absolute labour shortages. This confirms that mismatch phenomena are multidimensional and embedded within organisational structures [6]. The analysis also indicates role fragmentation, where employees cover multiple functional areas due to limited availability of specialised competencies. While this may increase short-term flexibility, it introduces systemic vulnerability under demand shocks. Such bottlenecks are consistent with broader restructuring pressures associated with the energy transition [1; 2]. From a broader perspective, these findings reflect low-carbon transition dynamics, where labour exposure varies across occupations and regions [3; 8]. At the organisational level, this is reflected in uneven demand sensitivity across qualification categories, particularly those linked to digital monitoring and energy efficiency.

Digitalisation further increases the need for cross-functional competencies. However, the results indicate that technological advancement does not automatically translate into structural readiness. Instead, insufficient alignment between HR configuration and technological change generates internal friction, consistent with existing research on digital transformation and organisational adaptability [11-13]. From a strategic perspective, workforce configuration can be interpreted as a dynamic capability. The observed concentration of overload in specific qualification clusters suggests limited reconfiguration capacity. This aligns with research emphasising the importance of HR flexibility and alignment with strategic objectives [15; 16]. Adaptive forecasting thus contributes not only to prediction but also to structural diagnostics, enabling identification of capacity constraints and risk zones. This supports the view that predictive analytics enhances strategic workforce planning by enabling more responsive decision-making [20].

Conclusions

1. The conducted analysis confirms that workforce planning challenges in the examined energy-sector organisation are primarily structural rather than purely quantitative. Adaptive forecasting reveals qualification-specific demand variability and uncertainty that remain undetected under static planning approaches.
2. The results demonstrate that workload dynamics are shaped by seasonal fluctuations and operational variability, which significantly affect qualification-specific labour demand. Structural gap analysis identifies imbalances between projected demand and available workforce capacity, with overload concentrated in specialised technical roles and underutilisation in other segments. Overall, workforce mismatch is configurational in nature, reflecting insufficient alignment between qualifications, roles, and dynamically changing operational requirements. This misalignment is further intensified by digitalisation, which increases demand sensitivity and reinforces the need for more flexible workforce configurations.
3. The main conclusions of the study highlight that workforce planning limitations are structural in nature, with hidden imbalances revealed only through dynamic modelling. Adaptive forecasting provides both predictive and diagnostic value by enabling the identification of demand variability and uncertainty. The analysis shows that structural gaps manifest as simultaneous overload in specialised roles alongside underutilisation in other areas. Overall, the proposed approach supports more responsive and data-driven workforce planning under dynamic conditions.

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Author contributions

Conceptualization, R.J.; methodology, R.J. and U.L.; software, R.J.; validation, R.J. and U.L; formal analysis, R.J; investigation, R.J. and U.L.; data curation, R.J.; writing – original draft preparation, R.J.; writing – review and editing, R.J. and U.L.; visualization, R.J.; project administration, U.L.; funding acquisition, U.L. All authors have read and agreed to the published version of the manuscript.

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