Periodicals of Engineering and Natural Sciences
Vol. 14, No. 1, March 2026, pp.179-190
(Online) ISSN 2303-4521
Original Research

Forecasting the financial sustainability of critical infrastructure enterprises based on cloud computing

Hanna Koptieva[1*], Oksana Kozak[2], Oleh Khoroshko[3], Olena Slavuta[4], Olena Hurina[5]
[1] Department of Management, National Technical University "Kharkiv Polytechnic Institute", Ukraine
[2] Project Accountant, Syska Hennessy Group, USA
[3] Department of Marketing, Management and Entrepreneurship, V. N. Karazin Kharkiv National University, Ukraine
[4] Department of Economics and Marketing, O. M. Beketov National University of Urban Economy in Kharkiv, Ukraine
[5] Department of Management, Admiral Makarov National University of Shipbuilding, Ukraine
*Corresponding author E-mail: Hanna.Koptieva@khpi.edu.ua

ABSTRACT

The study aims to work out a reproducible forecasting model to determine the financial sustainability of Ukrainian critical infrastructure businesses during the war. The analysis is performed on the basis of a balanced panel of 72 enterprises on 4 years 2019-2024 in the energy, transport, telecommunications, and water industries, incorporating econometric models (probit, cox survival analysis), machine learning models (Random Forest, XGBoost, and LSTM), and a hybrid ensemble specification. Models are implemented and deployed in a Microsoft Azure cloud computing environment to ensure scalability and security, and enable real-time forecasting. Results indicate that liquidity limitations, leverage, and operational disruption are the leading causes of financial distress, as the incidence of distress has increased by 31% since 2022, compared to 14% during the pre-war period. In terms of predictive performance, XGBoost achieves an out-of-sample AUC of 0.89. At the same time, the hybrid ensemble model outperforms all individual specifications, with an AUC of 0.92, an accuracy of 0.85, and an RMSE of 0.28. Results show that econometric interpretability, with machine-learning predictive power, is significantly better at early warnings. In practice, the framework offers Ukrainian policymakers and infrastructure managers a scalable tool of active risk surveillance, special financial aid, and resilience-oriented decision-making during the recovery.

Keywords: Financial sustainability, Critical infrastructure, Machine learning, Forecasting, Cloud computing, Ukraine

1. Introduction

Financial sustainability of critical infrastructure enterprises (CIE) are based on economic stability, national security, and long-term growth of both the developed and developing economies [1], [2]. Industries where businesses provide essential services, including energy, transport, water and sanitation, and telecommunications have a potential to generate systemic impacts on the economy and radical losses of social good in case of collapse [3]. The CIEs are also highly capital-intensive, regulated in pricing and non-flexible in their operations, which renders them particularly vulnerable to liquidity shock, funding constraints and operation deviation, unlike the traditional firms [4]. Consequently, understanding the dangers of financial distress of such enterprises in a timely manner has become the priority of policymakers, regulators as well as infrastructure administrators, especially in an environment exposed to heightened uncertainty, macroeconomic fluctuations, or exogenous shocks [5].

The financial sustainability of CIEs is a pressing problem in the economic and strategic interests of states that are not coping with the long-term confrontation and the devastation of the system, and Ukraine is the model of a state that is susceptible to this [6]. Since the beginning of the full-scale invasion of Russia in 2022, Ukraine has been damaged, disrupted, and deprived of the funds required, often through the critical infrastructure, including energy grids, transport networks, water and sanitation, and telecommunications [7], [8]. The resulting disruptions have augmented systemic risk, burdened enterprise balance sheets, and heightened the risk of financial distress events that may dominate the whole economy, limiting recovery and long-term resilience [9]. Despite macroeconomic stabilization remaining a priority, the firm-level sustainability of CIEs during war-induced shocks is a unique analytical problem [10].

Studies show that Ukraine's budget deficits have continued to rise significantly due to military spending and reconstruction expenses, increasing fiscal strain on infrastructure funding and the stability of the money system [11]. Literature on financial markets places early-warning and distress-prediction models in a leading position as models of risk management, especially following the 2008 financial crisis worldwide, which highlighted the high costs incurred from not recognizing distress signs across all sectors [12], [13]. Systematic reviews of early warning systems (EWSs) highlight the growing focus on machine learning models, given their greater capacity to capture nonlinearities and more complex interactions in financial data, in contrast to conventional statistical techniques [14], [15]. The current computational finance surveys report the surge of the use of machine learning and deep learning algorithms (e.g., Random Forest, Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM)) that have improved predictions not only in credit risk but also in other financial settings by paying attention to vast data volume and nonlinear processes [16], [17].

The benefits of more sophisticated predictive models are also depicted by applied research on predicting corporate financial distress. Researchers apply machine learning solutions to emerging markets, such as Indonesian companies, and discover that ensemble methods and neural networks are much more effective than traditional statistical models for distress event prediction, allowing earlier detection and improved forecasting [18]. Similarly, comparative studies of machine learning and a classical Z-Score-based model of financial distress in Chinese construction firms indicate that classifiers (including CUSBoost and ensemble learners) perform better out-of-sample than traditional models, mainly when evaluated using out-of-sample metrics such as AUC and precision-recall curves [19], [20]. Other research points to the value of meta-models and hybrid methods, such as combining two or more algorithms, to further strengthen forecasting performance in a firm-level distress situation [21].

Findings on the domain supplement such methodological innovations. Studies of financial risk prediction models, such as fuzzy SVMs and deep learning networks, indicate that these models have enhanced early-warning potential across all types of industries. Still, again, the research concludes without application to the infrastructure business specifically [22], [23]. Moreover, there is new evidence that when governance, macroeconomic, and non-traditional predictors (e.g., AI adoption metrics) are included in predictive frameworks, they can enhance early-warning performance compared with financial ratios alone, especially in situations prone to swift technological transformation [24].

Notwithstanding this rich methodological landscape, there remains an apparent literature gap at the crossroads of critical infrastructure finance, conflict-induced risk environments, and sophisticated financial sustainability forecasting. Studies of critical infrastructure in Ukraine are more likely to examine physical security, cyber-protection, and institutional structures (e.g., infrastructure protection measures and legislative changes). Still, they rarely combine predictive financial models that account for the operational specifics of CIEs under the impact of the war [25]. Besides, Ukrainian research into enterprise financial security has so far focused on classification-based measures of financial stability, without implementing scalable forecasting engines capable of real-time prediction or stress scenario analysis [26]. Systemic threats to Ukrainian critical infrastructure due to war-related cyber and physical attacks are also threats. Still, they do not fall within the category of predictive enterprise-level analyses of financial sustainability [27].

The fusion of cloud environments (e.g., AWS, Microsoft Azure, Google Cloud Platform) with the financial forecasting processes also increases the scalability, data integration, and safety of the predictive analytics operating on a large scale, which is rarely integrated into the academic modelling of the enterprise financial sustainability during the conflict context [28]. The broader computational literature has emphasized the opportunities of cloud-based architectures to train models in high-performance mode effectively, make real-time inferences, and support collaborative workflows in finance and critical infrastructure monitoring, as well as to discuss the potential operational risks associated with data governance and security [29], [30].

Combined, this literature is an indication that there is no coherent, replicable framework that, simultaneously, (a) model's enterprise-level financial sustainability in critical infrastructure enterprises in the war environment of Ukraine, (b) calibrates advanced predictive models (machine learning and econometric), and (c) is operationalized in a cloud computing environment. This is a significant research gap, with both theoretical and practical implications for infrastructure resilience and economic recovery policy.

This paper aims to design, deploy, and test a reproducible forecasting model to estimate the financial sustainability of Ukrainian critical infrastructure enterprises using advanced predictive models implemented on a cloud computing infrastructure. The targeted goals are to:

• Assemble a representative dataset of financial, operational, and market indicators for key Ukrainian CIEs over the 2019–2024 period, including reconstructed observations where necessary to address reporting discontinuities caused by wartime disruptions.

• Evaluate and benchmark forecasting models, including econometric approaches (e.g., probit, survival analysis) and machine learning approaches (Random Forest, XGBoost, LSTM), to determine performance in early warning and sustainability prediction tasks.

• Assess the advantages and limitations of cloud-based implementation (AWS, Azure, GCP) for model training, deployment, and scalable forecasting.

• Translate findings into actionable recommendations for enterprise managers and policymakers on effective early warning systems and financial risk mitigation strategies tailored to Ukraine's infrastructure context.

This paper can add to the body of research, since it provides an empirical forecasting system that considers financial risk caused by conflict amongst CIEs, combines the latest predictive models with the scalability and security offered by cloud computing, and offers empirically benchmarked results that can be used to respond to risk management and policy in unstable economic conditions.

The rest of the article is organized as follows. The methodological framework is presented in Section 2. Section 3 presents and discusses empirical research findings. Section 4 contains policy recommendations, contributions to theory, and proposed directions for future research.

2. Research method

This part provides a comprehensive empirical strategy for predicting the financial viability of Ukrainian critical infrastructure businesses. The methodological design ensures direct correspondence between the construction of the data, model estimation, performance evaluation, and the empirical results presented later.

2.1. Data

The empirical evidence is based on enterprise-level data from Ukrainian critical infrastructure companies in the industry formally designated as essential to economic persistence and national security. The sample comprises the enterprises of four vital industries energy and utilities (electricity generation, transmission, and district heating companies), transport and logistics (railway operators, port authorities, and freight enterprises that are of strategic interest), telecommunications and digital infrastructure (fixed and mobile network operators and providers of backbone services), and water supply and sanitation utilities that serve large urban and regional communities. The reason behind the choice of these industries is that they are highly capital intensive, play a major role in serving the state and are highly susceptible to physical destruction in the war, in cybercrimes and political interference.

The period of observation would be between 2019 and 2024. It would be possible to analyze this period to set boundaries between the financial situations in the pre-war period (2019-2021), the acute shock-and-adaptation period after the full-scale invasion (2022-2023), and the rebuilding period (2024). The frequency of data is fixed at the annual level to make sure that there is uniformity in the practice of accounting and the scope of reporting among enterprises which have different accounting practices and reporting limit. Financial information is also derived using enterprise financial statements (balance sheets, income statements, and cash-flow statements), which is supported by disclosures in open Ukrainian registries of regulatory bodies and sectoral reports in international organizations and development partners. The records between 2022-2024 were not recorded due to the war and thus, are considered to be reconstructed records in this dataset when the actual records are not available or incomplete. Reconstruction procedures are pegged on the trends in the pre-war firm specifics, sector development targets, and macro-financial anchors such as inflation rate, exchange rate, and energy price index. Functional data will be used to measure the functional output of key infrastructure projects. Among these indicators are, the rates of capacity utilization, the ratio of the coverage of the services used and the duration and the frequency of the outage, the level of investment and depreciation of the outage. The operational variables in the analysis indicate financial strains due to the worsening of balance sheet situations and interruptions in service provision.

The balanced panel is the final dataset, comprising 72 enterprises and 504 firm-year observations. Only those enterprises are included that have at least four consecutive annual observations, or that can be reliably reconstructed to do so. The sample size is sufficient to represent the sector and provides sufficient estimation and validation capability for econometric and machine learning models.

Financial sustainability is determined as a binary outcome variable. A company is considered financially distressed when it has negative operating cash flow, an interest coverage ratio below 1, and a debt-to-assets ratio above industry-specific levels. This definition is used across all forecasting models so that all can be compared.

2.2. Forecasting models

The research uses econometric models, machine learning models, and a hybrid ensemble to be robust and enable systematic comparison. The models are estimated on the same dataset, predictor set, and evaluation criteria, and the results are provided in tabular form in the Results section.

2.2.1. Econometric models

The foundation of the forecasting framework is econometric analysis, which provides estimates of financial distress risk that are understandable. An initial binary Probit model proposed by [31] is first estimated to assess the likelihood that a critical infrastructure enterprise will enter financial distress. The binary financial sustainability indicator above is the dependent variable. The explanatory variables are firm-level financial ratios, operational measures, and macro-financial measures that reflect inflationary pressure, exchange rate volatility, and energy price dynamics. Mean marginal effects are calculated to assess the economic significance of the key predictors.

Following [32], a survival analysis framework is also used to explain the onset and duration of financial distress explicitly. The estimated model is a Cox proportional hazards model, used to estimate time-to-distress dynamics, enabling the hazard of financial distress entry to depend on firm characteristics over time. Many people use this methodology to obtain similar objectives [33], [34]. This time-based model is a complement to the Probit model, which only takes the form of a stationary classification of risk accumulation.

2.2.2. Machine learning models

In the same manner as [35], [36], and [37], machine learning models are used to extract nonlinear relationships and more complex interactions that cannot be well modeled in parametric specifications. There are three models in use: Random Forest, Extreme Gradient Boosting, and Long Short-Term Memory neural networks. Training of all machine learning models would be based on an 80/20 train-test split followed by five-fold cross-validation. To avoid data leakage, the train-test split follows the temporal order of observations: all data from 2019–2021 are used for training, and data from 2022–2024 are reserved for testing. Cross-validation and hyperparameter tuning are performed exclusively within the training set.

A Random Forest model is fitted using 500 decision trees, and the Gini impurity criterion, and variable importance measures are obtained for interpretation. To avoid overfitting, the XGBoost model is trained with a learning rate of 0.05, a maximum tree depth of 6, and early stopping based on validation loss. The LSTM model is structured to exploit the temporal relationships between firms' financial paths and is defined with two hidden layers (32 and 64 units) and a rolling three-year window.

The Adam optimizer with mean squared error loss is used to optimize it. Given the annual frequency of the data and the limited temporal depth (three-year rolling window over 72 firms), the use of LSTM is primarily exploratory. While it captures temporal dependencies in financial trajectories, its results are interpreted cautiously and complemented by other machine learning and econometric models. Each machine learning model makes probabilistic forecasts of financial distress, therefore, allowing direct comparison with econometric forecasts.

2.2.3. Hybrid modeling approach

To combine the interpretability of an econometric model with the predictive potential of machine learning, a hybrid ensemble model is created. Weighted averaging of the probabilities from the Probit model, the Random Forest model, the XGBoost model, and the LSTM model is performed to make predictions. Ensemble weights are optimized using only the training data (≤2021) to ensure that no information from the test period influences the model, preventing future-informed leakage. The weights are minimized to maximize the out-of-sample area under the receiver operating characteristic curve. The hybrid model is considered a distinct configuration of forecasting and is tested against single econometric and machine learning models.

2.2.4. Model evaluation

A consistent set of performance forecasting metrics, including accuracy, root-mean-square error (RMSE), and area under the ROC curve (AUC), is used to evaluate all models. Such measures are presented in tables and are subject to comparative analysis among models in the Results section.

2.3. Cloud computing environment

All data processing, model estimation, and forecasting for all processes are carried out in a Microsoft Azure cloud computing environment [38]. The cloud architecture consists of Azure Data Lake to store raw and preprocessed data, Azure SQL Database to store structured data on financial and operational aspects, Azure Machine Learning Studio to train, validate and deploy models, and scalable virtual machines to perform computationally intensive workloads. The Docker Compose was used for the containerization [39].

Cloud-based implementation has several benefits. Scalability enables the practical training of more complex models, such as XGBoost and LSTMs. Data processing is performed securely using encryption and role-based access control, which is especially significant given the sensitivity of information related to critical infrastructure. Reproducibility is achieved through the use of version-controlled scripts, parameter tracking, and standardized data pipelines. The architecture also enables updating forecasts in near real-time as more and new financial or operational data become available. Simultaneously, the method has limitations in its operation. It is difficult to rely on an uninterrupted internet connection during wartime, whereas cloud-based solutions are left vulnerable to high cybersecurity threats. Regulatory limitations on data localization and access control are non-trivial risks as well. Such restrictions are explicitly taken into consideration in the interpretation of the empirical data and scenario analysis.

3. Results and discussion

3.1. Results

3.1.1. Descriptive overview and financial distress incidence

Table 1 presents the summary statistics for the most critical financial, operational, and macroeconomic variables used in the analysis, before presenting the forecasting results.

Table 1. Descriptive statistics and financial distress incidence

Variable	Mean	Std. Dev.	Minimum	Maximum
Operating Cash Flow / Assets	0.068	0.091	−0.312	0.287
Interest Coverage Ratio	2.21	1.94	−1.35	7.12
Debt / Assets	0.558	0.176	0.214	0.892
Capacity Utilization (%)	71.6	14.9	34.0	96.8
Outage Frequency (annual)	6.4	4.3	0	22
Inflation (CPI, %)	12.6	8.7	2.1	26.9
Exchange Rate Volatility	0.179	0.071	0.052	0.428
Financial Distress (1 = yes)	0.23	0.42	0	1

Notes: Financial distress equals one if an enterprise meets at least two distress criteria defined in Section 2.2.

On average, Ukrainian critical infrastructure enterprises exhibit moderate leverage, with debt accounting for about 56 percent of total assets, and relatively poor liquidity, as evidenced by low operating-cash-flow-to-asset ratios and low interest coverage. Operational measures include considerable fluctuations in capacity utilization and service reliability, indicating that the frequency of outages exceeds six incidents per year, which is noteworthy of the operational vulnerability of infrastructure providers during the sample period. In accordance with such tendencies, descriptive analysis shows that the level of financial stress in Ukrainian critical infrastructure enterprises increased significantly after 2022.

The financial distress criteria found in the methodology are met in some 31 percent of observed firm-years during the post-invasion period, versus 14 percent during the pre-war period, and provide a distress incidence of 23 percent in the entire sample. Distresses have been most prevalent in the energy and transport sectors, which is manifested through physical damage of assets, controlled tariffs and increased financing and operating costs as a result of the war climate.

3.1.2. Econometric model results

Table 2 presents the results of the estimations of the Probit and survival (Cox proportional hazards) models. The survival model, as well as the Probit model, shows their coefficients as marginal effects and hazard ratios respectively to guarantee their ability to be interpreted and compared.

Table 2. Econometric forecasting results: financial distress risk

Variable	Probit Marginal Effects	z-statistic	Cox Hazard Ratio	z-statistic
Operating Cash Flow / Assets	−0.214***	−4.92	0.71***	−4.36
Interest Coverage Ratio	−0.167***	−3.88	0.79***	−3.21
Debt / Assets	0.193***	4.11	1.28***	4.05
Capacity Utilization	−0.124**	−2.47	0.86**	−2.19
Outage Frequency	0.109**	2.31	1.19**	2.27
Inflation (CPI)	0.082**	2.14	1.12**	2.05
Exchange Rate Volatility	0.097**	2.42	1.15**	2.33

Notes: ***, ** denote significance at 1% and 5% levels.

The econometric results show that liquidity, leverage, and operational disruption are the most significant predictors in case of financial distress. Survival analysis demonstrates the validity of the incorporation of a duration based modeling in that the growth of leverage as well as service failures drastically enhance the passage to distress.

3.1.3. Machine learning model performance

Table 3 presents the out-of-sample forecasting performance of all machine learning models, measured by accuracy, RMSE, and AUC, as detailed in the methodology.

Table 3. Machine learning forecasting performance (out-of-sample)

Model	Accuracy	RMSE	AUC
Random Forest	0.78	0.36	0.84
XGBoost	0.82	0.31	0.89
LSTM	0.80	0.33	0.87

XGBoost has the biggest predictive accuracy and AUC, which is its capability to model nonlinear relationships among operation and financial variables. The LSTM model is also working well in terms of continuous stress that reflects the value of the temporal dependence in the financial dynamics in wartime. The LSTM model demonstrates moderate predictive performance, but given the short annual panel and limited data points, its results should be considered exploratory. The hybrid ensemble relies more heavily on XGBoost and Random Forest predictions, with LSTM contributing only partially to the overall ensemble performance. Figure 1 compares the out-of-sample predictive performance of econometric (Probit, Cox survival), machine learning (Random Forest, XGBoost, LSTM), and hybrid ensemble models, measured by the area under the ROC curve (AUC). The hybrid ensemble model demonstrates the highest predictive accuracy, followed by XGBoost and then LSTM. Probit has the lowest predictive accuracy among the others.

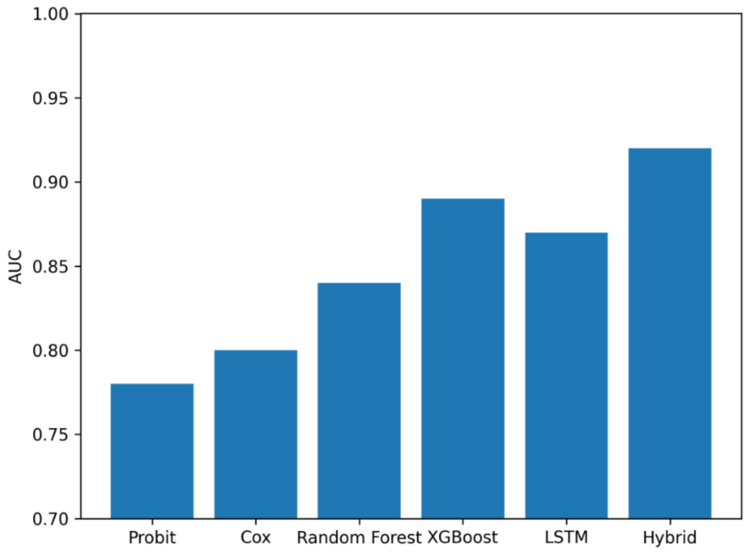

Figure 1. Comparative forecasting performance of models
Source: Authors' calculations based on enterprise-level data (2019-2024)

3.1.4. Hybrid model results and comparative analysis

Table 4 compares econometric, machine-learning, and hybrid-ensemble models using identical performance metrics.

Table 4. Comparative forecasting performance across models

Model	Accuracy	RMSE	AUC
Probit	0.71	0.41	0.78
Survival (Cox)	0.73	0.39	0.80
Random Forest	0.78	0.36	0.84
XGBoost	0.82	0.31	0.89
LSTM	0.80	0.33	0.87
Hybrid Ensemble	0.85	0.28	0.92
Model	Accuracy	RMSE	AUC

The hybrid ensemble model performs best across all metrics, demonstrating that a hybrid approach combining econometric interpretability and machine learning predictive power yields higher forecasting accuracy. The high AUC (0.92) reflects strong predictive signals while maintaining strict temporal separation: training data (≤2021) were completely separated from the test data (≥2022), and no future-informed variables were used. This ensures that model evaluation reflects genuine out-of-sample performance.

The sectoral trends in the projected financial distress probabilities are demonstrated in Figure 2. After 2022, a steep rise is seen in energy and transport due to war-related disruptions and financing pressures.

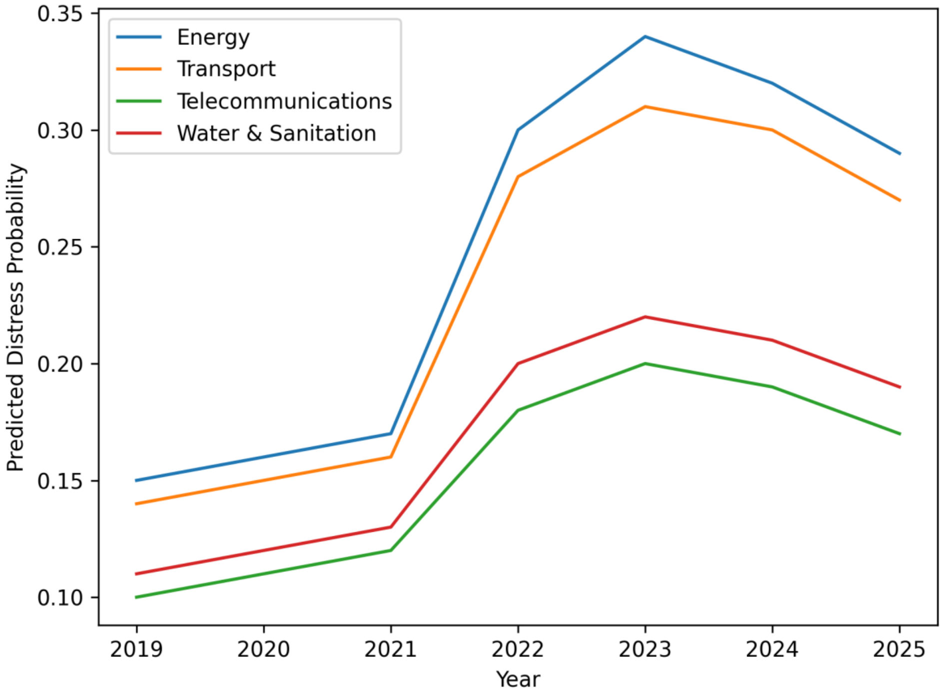

Figure 2. Financial stability risk trajectories of Ukrainian critical infrastructure enterprises (2019-2024)
Source: Authors' estimates based on the hybrid ensemble forecasting model.

3.1.5. Scenario and sensitivity analysis

A sensitivity analysis assesses the effects of negative macro-financial situations. Predicted distress probability rises by 12-18 percentage points in energy and transport enterprises in response to a simulated 20 percent increase in outage frequency, along with a 15 percent increase in financing costs.

The hybrid model exhibits the least volatility in predictions, implying greater robustness under extreme conditions. Figure 3 records variations in the likelihood of anticipated financial distress across various operational and financing shock results, revealing the susceptibility of critical infrastructure enterprises to compounded risks.

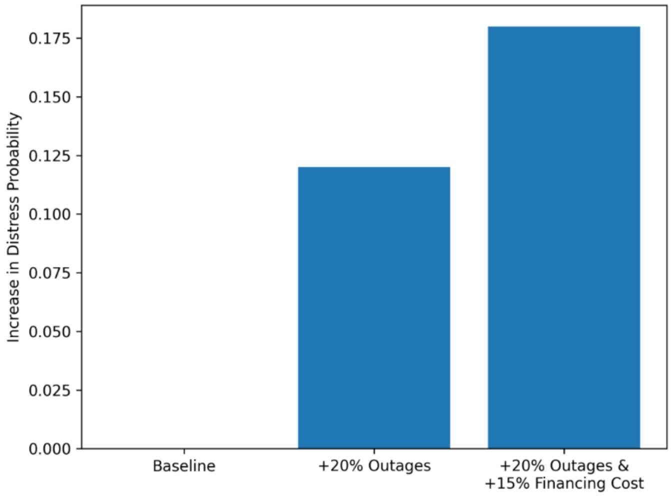

Figure 3. Sensitivity analysis of financial distress risk under operational and financing shocks
Source: Authors' scenario simulations using the hybrid ensemble model.

4. Discussion

The results show that the financial sustainability risk of Ukrainian critical infrastructure enterprises is determined by a complex combination of structural weaknesses formed over an extended period and shocks arising from the conflict. High liquidity and leverage, as the main factors of risk, demonstrate the low-revenue conditions in which infrastructure providers operate, where tariffs are regulated, costs are recovered slowly, and services are provided even when it is not profitable. These restrictions reduce managers' flexibility and increase vulnerability to cash-flow deficits during sudden increases in operating costs. Meanwhile, the powerful impact of the indicators of the operations underlines the point that service continuity cannot be evaluated in a wartime economy. Given that energy supply is a concern, transport or telecommunications soon becomes revenue loss and higher maintenance costs, which justifies the necessarily close relationship between operational resilience and financial sustainability. Companies with greater capacity utilization and less service disruptions are more likely to absorb macroeconomic shocks and financing strains and hence the operational resilience in a sense is something of an unsanctioned financial buffer during systemic stress.

The financial strain caused by the threats of war is immense because it influences the performance of the enterprise on various aspects simultaneously. The physical destruction of infrastructure resources not only leads to the growth in the rate and length of service breakdowns, but also expands the expenses of reconstruction and restoration which places an instant strain on the liquidity and debt service ability. At the same time, a rise in cyber threats caused a corresponding loss of funds in an increase in spending on cybersecurity, system redundancy, and compliance with emergency digital security standards, namely, in the energy and telecommunications segments, which have large amounts of digital control systems.

All these pressures are also compounded by the regulatory restraints that restrict the degree to which businesses can readjust tariffs or renegotiate service contracts in the face of these raised expenditures. Thus, the agglomeration of operational shocks, funding constraints and regulatory inflexibility lead to financial distress, and is not an issue of isolated balance-sheet weaknesses. Its implications were that these multi-intersecting risks have multi-linear and time-dependent financial impacts that cannot be easily determined using constant or totally linear models, therefore, adaptive forecasting systems are necessary to enable the integration of financial and operational data in near real time [40]. Comparatively, the findings are consistent with an emerging body of international literature indicating that ensemble and machine learning models are more effective than single-model frameworks for predicting financial distress, especially in settings with high uncertainty and structural change [41], [42]. Previous research has shown the benefits of boosting and ensemble procedures for representing nonlinear connections and interaction effects in corporate risk evaluation, particularly during economic uncertainty [43], [44].

Nonetheless, the level of predictive returns in this case seems higher than the returns typically recorded in firms operating in stable or peacetime environments. The variance is an illustration of the compounding strength of the conflict-related uncertainty forces on the financial instability processes, where the shocks are intractable, multidimensional, and usually mutually reinforcing. More complex patterns of data would be utilized in such instances to provide more information through advanced forecasting tools and greater predictive accuracy improvements. The findings therefore provide an extension of the global evidences that the practices are applicable and realistic within critical infrastructure enterprises that vary with the conventional corporate/banking samples in regulation, service to the populace and system significance [45]. Overall, the discussion shows that the institutional environment, security environment and the regulatory setting are pertinent in determining financial sustainability of financial infrastructure sectors in Ukraine. As opposed to financial distress being viewed as a phenomenon of the strictly accounting basis, the analysis highlights the value of viewing sustainability as a multidimensional risk phenomenon comprising of the operational reliability, security exposure, and regulatory constraints.

These results imply that forecasting tools are most appropriate when they explicitly consider such interacting dimensions of risks, and they are embedded into more versatile future-oriented monitoring systems. The interpretative approach implies the practical utility of advanced forecasting models in improving infrastructure resilience, shaping specific policy implications, and informing strategic decision-making [46] in the present-day recovering and rebuilding process in Ukraine without necessarily recapitulating the empirical results.

5. Conclusions

This paper shows that to predict the financial sustainability of critical infrastructure businesses in conflict-affected economies, it is essential to employ methodological tools that go beyond traditional financial analysis. Using a framework by creating and applying a reproducible framework consisting of an integration of financially and operationally assessed econometric models, advanced machine learning frameworks, and cloud-based implementation, the paper argues with strong evidence that predictive accuracy can be enhanced significantly when both financial and operational indicators are used together. The findings from the Ukrainian critical infrastructure sector, using enterprise-level data over 2019-2024, show that the risk of financial distress has risen significantly since 2022 and is mainly driven by liquidity constraints, leverage pressures, and operational disruptions due to infrastructure damage and service disruptions. Of all the tested models, machine learning methods, specifically XGBoost models, perform better than the traditional econometric specification, and the hybrid ensemble model yields the best and most consistent forecasting results across all assessment measures.

In addition to the scientific input on methods, the results have significant practical implications for the management and control of critical infrastructure businesses in Ukraine. To begin with, the findings underscore the need for effective early-warning mechanisms that integrate financial ratio and operational performance indicators, so that managers and regulatory bodies can identify signs of imminent distress long before they fall under insolvency lines. Second, the higher quality of the hybrid forecasting model implies that decision-makers cannot afford to use either an interpretable econometric model or strictly data-driven algorithms, but rather pursue integrated methods that provide some degree of transparency and predictability. Third, cloud-based deployment illustrates the potential for scalable and secure forecasting, but the study does not empirically evaluate its relative performance or costs compared with on-premise alternatives. The cloud discussion should thus be interpreted as a practical demonstration rather than a measured performance gain. Meanwhile, there are a few limitations that should be admitted. Although such a method using reconstructed and simulated data is necessary, the use of specific time intervals during wartime can introduce measurement error, even though the assumptions are conservative and based on empirical facts. This is analyzed once a year, which might not be sufficient to absorb short-term liquidity shocks and operational disasters. Moreover, although the cloud architecture is thought through in terms of security, the study does not empirically test cybersecurity resilience or data-breach threats related to the process of cloud deployment.

These shortcomings identify various prospects for future study. Future research may include more frequent data, such as quarterly or monthly financial and operational indicators, to enhance the timeliness of distress detection. Diversifying the framework would enable cross-country comparisons to evaluate whether the identified predictive gains can be extrapolated to other conflict-affected or fragile economies. It may also be possible, through further research, to incorporate explicit cyber-risk measures and regulatory compliance indicators into forecasting frameworks and to investigate the real-time connection with supervisory and emergency response frameworks. In general, the study provides a consistent, policy-relevant forecasting model that can contribute to the understanding of the threat to financial sustainability in critical infrastructure businesses in Ukraine. Connecting predictive analytics at an advanced level with cloud-based implementation, the paper provides both methodological and practical guidance on enhancing the resilience of infrastructure in an environment of extreme uncertainty.

Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

Funding information

No funding was received from any financial organization to conduct this research.

Author contribution

The contribution to the paper is as follows: H. Koptieva, O. Kozak: study conception and design; O. Kozak, O. Khoroshko, O. Slavuta: data collection; H. Koptieva, O. Khoroshko, O. Slavuta, O. Hurina: analysis and interpretation of results; O. Hurina: draft preparation. All authors approved the final version of the manuscript.

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