Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 4, August 2025, pp. 3121~3132
ISSN: 2302-9285, DOI: 10.11591/eei.v14i4.9358

A novel MPK optimization framework for financial data analysis incorporating complexity and uncertainty management

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Article Info

Article history:

Received Sep 25, 2024
Revised Jun 8, 2025
Accepted Jul 23, 2025

Keywords:

Input optimization function
Multi-objective complexity prediction model
Prediction analysis
Regression output value optimization function
Uncertainty optimization function

ABSTRACT

In a competitive environment, the ability to scale quickly and successfully is a critical need. This research proposes a new framework using multi-objective complexity prediction model (MPK) for financial data analysis, including complexity and uncertainty management. This model integrates input, uncertainty, and output optimization functions (OOFs) (input optimization function (IOF), uncertainty optimization function (UOF), and OOF) to predict complex output values under dynamic business conditions. Model evaluation is carried out using performance metrics, namely mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R^2 score. The evaluation results show that this model has an MSE value of 20.112, an RMSE of 2.267, and an MAE of 2.351, reflecting a low prediction error rate and high accuracy. In addition, the R^2 value of 0.884259 indicates that this model is able to explain around 88.4% of the variability in the output data, indicating its ability to capture complex data patterns. Thus, the proposed MPK model is effective in predicting output values in complex business scenarios and can be applied for strategic decision-making under conditions of uncertainty.

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1. INTRODUCTION

Financial data analysis is a crucial component in the practice of financial management, investment decision-making, risk evaluation, and strategic planning inside organizations [1]-[3]. The increasing complexity of financial markets and the growing amount of available data necessitate the development of more advanced and flexible financial data analysis techniques. Conventional approaches like technical and fundamental analysis frequently encounter constraints when confronted with rapidly shifting market dynamics and significant levels of uncertainty [4], [5]. Technical analysis primarily relies on historical price and volume patterns, disregarding fundamental and external factors. In contrast, fundamental analysis concentrates on company performance as indicated by financial statements and macroeconomic conditions, but it is less sensitive to short-term market fluctuations and current investor sentiment. Furthermore, both methods frequently overlook the non-linear correlations among different financial and economic variables that mutually impact one another. However, despite the development of big data-based approaches to address these constraints, these models remain less capable of managing market uncertainty and intricate interconnections among factors [6], [7].

This study introduces the multi-objective complexity prediction model (MPK) optimization model as a new method for financial data analysis combining three key metrics: input optimization function (IOF), uncertainty optimization function (UOF), and output optimization function (OOF). This model is de-signed to optimize financial data analysis more effectively and provide deeper insights into complex market behaviour [8]. IOF focuses on optimizing the use of input resources such as stock prices, trading volumes, interest rates, and macroeconomic indicators, with the aim of identifying the most efficient combination of inputs to achieve optimal results [9]. UOF considers market uncertainty caused by volatility, liquidity, systemic risk, and external events such as changes in government policy or geopolitical events [10]. It is designed to predict possible outcomes based on different market scenarios [11]. Meanwhile, OOF optimizes output values by considering desired performance such as maximizing profits, reducing risks, or achieving a balance between growth and stability [12], [13].

This work uses a number of statistical assessment metrics, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R-square (R^2), to ensure the validity and precision of the proposed MPK model. RMSE measures the average difference between the predicted values generated by the model and the actual observed values [14]-[16]. A lower RMSE value indicates that the model exhibits superior predictive accuracy for financial data. A statistical measure called MSE measures the mean square of prediction errors [17], [18]. It places a higher penalty on large errors, making it valuable for assessing the model's ability to handle extreme predictions. MAE measures the average absolute error between the predicted values and the actual values. MAE provides a direct view of the average error without considering the error direction (positive or negative) [19], [20]. Meanwhile, the coefficient of determination (R^2) measures the extent to which the model can account for data variability. A higher R^2 value indicates that the model is more effective in explaining the relationship between input and output variables. This study contributes by introducing a more adaptive and responsive MPK optimization model to complex financial market dynamics [21], [22]. This study provides a more robust framework for financial data analysis under uncertainty. The model is expected to help decision-makers in the financial sector to make more informed, adaptive, and data-driven decisions [23].

2. METHOD

The first step is the collection and preparation of financial data from relevant sources, followed by feature engineering to identify critical variables in the model. A MPK model is developed using a state-space model to model the variables and external disturbances. Then, IOF, UOF, and OOF are applied to optimize resource utilization, manage risk, and maximize financial outcomes. A heuristic approach is applied to optimize inputs in IOF. To manage uncertainty in UOF, a probabilistic model is used to predict various outcomes and quantify risk. An AI-driven optimization approach is applied in OOF to maximize desired outputs, such as profit or a balance between growth and stability. These three functions are integrated into a multi-objective optimization framework. The model is trained and tested on historical and synthetic data in various market scenarios and then evaluated using metrics such as MSE, RMSE, MAE, and R^2 to ensure accuracy. The results of the analysis are interpreted to provide insights to decision-makers regarding risk management and investment strategies in a complex market environment. Can be seen in Figure 1.

2.1. Data input

Table 1 shows the distribution and variability of data used for financial predictive analysis and risk optimization. Variables like stock prices and interest rates have stable distributions with low variation, making them ideal for input optimization. In contrast, variables such as trading volume and environmental impact show high variability, requiring special treatment to manage risk. The MPK model can utilize this data through three main functions. IOF focuses on stable variables to increase prediction accuracy, UOF handles variables with high variation to mitigate risk, and OOF maximizes variables such as profit and sustainability metrics.

2.2. Combination of MPK model with complexity prediction optimization formula

Explains the combination of the MPK model with a complexity prediction optimization formula through mathematical analysis to connect control vectors (u_k) state vector (x_k) and results (y_k).
Given a basic optimization model [24]:

$$\begin{aligned} x_{k+1} &= A_k x_k + B_k u_k + E d_k y_k = C x_k + D u_k \\ y_k &= C x_k + D u_k \end{aligned} \tag{1}$$

This (1) shows how the state of the system x_{k+1} at time $k+1$ is influenced by previous states x_k control vectors u_k and external disturbances d_k. where, x_k is state vector at time k; u_k is control vector at time k; d_k is disturbance vector at time k; A_k, B_k, E presented parameter matrix for state models; and C, D presented parameter matrix for the output model.

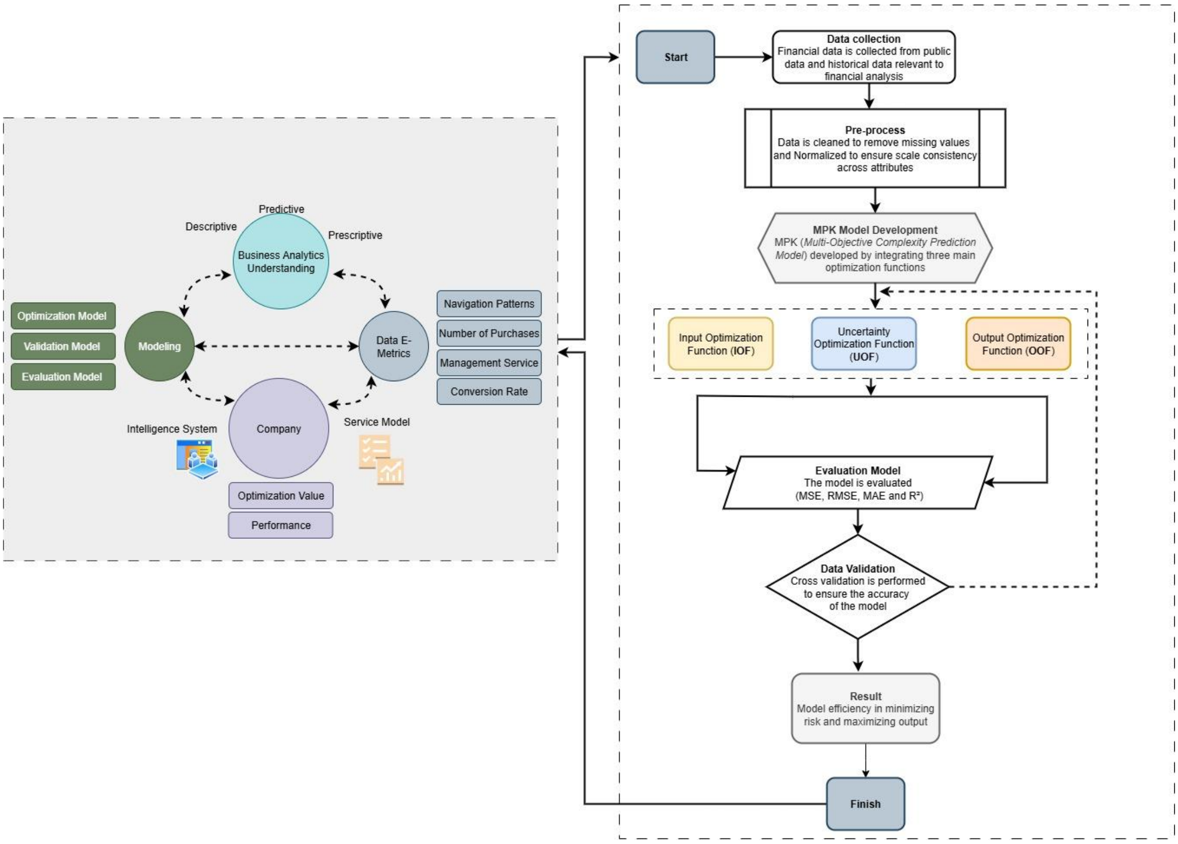

Figure 1. Research methodology

Table 1. Statistical summary of financial dataset

Statistic	Stock prices	Trading volume	Interest rates (%)	Profit	Risk index	Opportunity index	Environmental impact	Social impact	Sustainability metric
Count	10	10	10	10	10	10	10	10	10
Mean	151.35	1.050	2.55	1.254	0.646	0.328	473.5	307.5	8.98
Std	2.56	80.277	0.16	33.784	0.065	0.056	18.265	17.360	0.74
Min	147.80	950	2.30	1.200	0.55	0.25	450	280	7.90
Percentile	149.49	992.5	2.43	1.236	0.60	0.293	460	296.25	8.35
Median	151.00	1.050	2.55	1.255	0.645	0.30	470	305	8.90
Percentile	153.25	1.107	2.70	1.278	0.70	0.375	490	320	9.45
Max	155.78	1.200	2.80	1.300	0.75	0.42	500	335	10.00

Model derivatives of control vectors u_k, this analysis aims to measure the sensitivity of the system to changes in the control vector:

– Derivative of x_{k+1} to u_k

$$\frac{\partial x_{k+1}}{\partial u_k} = \frac{\partial(A_k x_k + B_k u_k + E d_k)}{\partial u_k}$$
$$\frac{\partial x_{k+1}}{\partial u_k} = B_k \quad (2)$$

showing that the influence u_k on the next state of the system x_{k+1} is mediated only by the parameter matrix B_k.

– Derivative of y_k to u_k

$$\frac{\partial y_k}{\partial u_k} = \frac{\partial (Cy_k + Du_k)}{\partial u_k}$$
$$\frac{\partial y_k}{\partial u_k} = D \tag{3}$$

indicates that the direct influence u_k at the system output y_k completely depends on the matrix parameters D. Model derivation of state vectors x_k.

This section measures the relationship between the current state and the system outcome:

– Derivative of x_{k+1} to x_k

$$\frac{\partial x_{k+1}}{\partial x_k} = \frac{\partial (A_k x_k + B_k x_k + Ed_k)}{\partial x_k}$$
$$\frac{\partial x_{k+1}}{\partial x_k} = A_k \tag{4}$$

shows that changes to the current state x_k impact the next state x_{k+1} through the matrix A_k.

– Derivative of y_k to x_k

$$\frac{\partial y_k}{\partial x_k} = \frac{\partial (Cx_k + Du_k)}{\partial x_k}$$
$$\frac{\partial y_k}{\partial x_k} = C \tag{5}$$

explains that the system output y_k is influenced byx_k through the parameter matrix C.

2.3. Combining complexity optimization functions

Explains how optimization functions are combined in the MPK model to handle various aspects of complexity and uncertainty in financial data analysis. The following is an explanation of the main elements:

$$MPK = \max\left(\sum_{i=1}^{n} W_i \times IOF_i + \sum_{j=1}^{m} V_j \times UOF_j + \sum_{k=1}^{p} X_k \times OOF_k\right) \tag{6}$$

$$x_{k+p} = A_k^{p-1} B_x u_k + A_k^{p-2} B_k u_{k+1} + \cdots . + A_k B_k u_{k+m-1} + A_k^{p-1} Ed_k + A_k^{p-2} Ed_{k+1} + \cdots + A_k Ed_{k+p-2} + Ed_{k+p-1} \tag{7}$$

where, W_i is weights for IOF; V_j is weights for UOF; X_k is robot for OOF; IOF_i is IOF; UOF_j is UOF; and OOF_k is OOF.

Definition of joint optimization function,

– IOF with state complexity:

$$IOF_i = \min\left(\frac{Resource\ Usage}{Expected\ Output}\right) + ||x_{k+1} - x_k|| \tag{8}$$

IOF measures the efficiency of resource use against expected output, while minimizing system state changes.

– UOF with state complexity:

$$UOF_j = \min\left(Risk - Opportunity + \left||A_k x_k - x_{k+1}|\right|\right) \tag{9}$$

UOF manages uncertainty by minimizing risks, exploiting opportunities, and ensuring system state changes remain under control.

– OOF with state complexity:

$$OOF_k = \max\left(\frac{Profit - Environmental\ Impact - Social\ Impact}{SustainabilityMetric}\right) + \left||Cx_k + Du_k - y_k|\right| \tag{10}$$

OOF maximizes output value (profitability), by considering environmental and social impacts and ensuring consistency between model predictions and actual results.

– Development of joint optimization model

$$MPK = \max \left(\sum_{i=1}^{n} W_i \times IOF_i(x_{k+1}) + \sum_{j=1}^{m} V_j \times UOF_j(x_{k+1}, A_k x_k) + \sum_{k=1}^{p} X_k \times OOF_k(y_k, Cx_k)\right) \tag{11}$$

This equation combines all the optimization functions (IOF, UOF, and OOF) with relevant weights to obtain an optimal solution that considers input efficiency, uncertainty, and output results.

3. RESULT AND DISCUSSION

3.1. Contribution model

x_{k1}, x_{k2}, x_{k3} describe the state values at time k and reflect the initial conditions of the input analysis in the model. $x_{k11}, x_{k12}, x_{k13}$ predict the state of the system at time $k+1$ after applying the prediction or optimization model. Shows the state of the system changes in the future based on the control parameters. y_k represents the predicted output of the model at time k. The output is in the form of profit, loss, and performance metrics from the model prediction. u_{k1}, u_{k2}, u_{k3} indicate the control variables in the system to direct or change the state towards the desired outcome. d_{k1}, d_{k2}, d_{k3} reflect external disturbances affecting the state of the system at time k. External risk factors such as market fluctuations, policy changes, or unexpected events affect the model outcome. Table 2 summarizes the variables in the prediction model dealing with complexity and uncertainty. The state vector describes the state of the system, while the control vector guides the system towards the desired outcome. The disturbance vector reflects external risks or uncertainties that may impact the outcome. The model output shows how the system is predicted to behave based on these inputs.

Table 2. State, control, and disturbance data for outcome prediction and financial optimization

x_{k1}	x_{k2}	x_{k3}	x_{k11}	x_{k12}	x_{k13}	y_k	u_{k1}	u_{k2}	u_{k3}	d_{k1}	d_{k2}	d_{k3}
0.37454	0.95071	0.73199	0.37910	0.88555	0.94639	222.937	0.05476	0.33520	0.80285	0.26560	0.12952	0.88875
0.59866	0.15602	0.15599	0.66205	-0.04650	0.17464	0.56824	0.00463	0.33350	0.39817	0.95565	0.86213	0.80952
0.05808	0.86618	0.60112	-0.0081	0.95142	0.52186	173.171	0.53740	0.91986	0.34635	0.65524	0.55086	0.08699
0.70807	0.02058	0.96991	0.69660	0.07108	105.649	183.423	0.34695	0.73750	0.45222	0.40845	0.37269	0.25975
0.83244	0.21234	0.18183	0.71241	0.17889	0.13433	0.81526	0.22461	0.45244	0.14086	0.72342	0.49588	0.08105

In Table 3 each element in matrix A shows a linear relationship between the current and future states in the system being analyzed. Matrix functions A_k is a transition parameter matrix that describes the linear relationship between the current state of the system x_k and the next state of the system x_{k+1}. This matrix determines how much influence each element has in x_k against the elements in x_{k+1}, which controls the internal dynamics of the system that does not involve external control or interference. Table 4 provides the state space model parameters used in predicting output based on system states. The C matrix is an output parameter matrix that determines the linear relationship between the system state x_k and the system output y_k. It maps the elements in x_k to the elements y_k. The C matrix is important in determining how changes in the system's internal variables (states) translate into changes in output.

Table 3. Parameters of matrix A_k

A_{k1}	A_{k2}	A_{k3}
0.45220	0.93388	0.31616
0.50723	0.04157	0.14834
0.98663	0.96512	0.00494

Table 4. Parameters of matrix C

C_{k1}	C_{k2}	C_{k3}
0.95181	0.63912	0.86792
0.45474	0.51560	0.48885
0.66686	0.13965	0.02997

Table 5 explains how the weights of various optimization functions (IOF, UOF, and OOF) are used to manage resource usage and achieve output. Where higher weights indicate that the optimization function has a greater influence in the decision-making or optimization process. A high V weight (0.96991 in the second row) indicates that uncertainty management (UOF) is very important in the scenario. Resource usage and expected output describe the relationship between input and output being optimized. If resource usage is higher (2,676,230,579 in the third row), but the expected output is lower (1,494,349,528), this indicates potential inefficiencies in resource management that need to be further optimized. Table 6 shows how various risk, opportunity, profit, and impact factors are measured and optimized in the business optimization model. where risk and opportunity indicate the trade-off between risk and opportunity in the model. Higher risk values with lower opportunity indicate a risky but less profitable situation. Profit, environmental impact, and social impact provide the financial and non-financial impacts of the decision. A scenario with high profit but low environmental or social impact would be more desirable in multi-objective optimization. The sustainability metric is used to assess how sustainable a strategy is in the long term. Higher values indicate a more sustainable decision. Results are based on (1)-(5).

Table 5. Weight and resource usage

Weight W (IOF)	Weight V (UOF)	Weight X (OOF)	Resource usage (IOF)	Expected output (IOF)
0.30793	0.67343	0.67260	1,354,299,579	2,389,228,439
0.70468	0.96991	0.44375	2,385,251,904	1,866,496,057
0.20185	0.09390	0.86814	2,676,230,579	1,494,349,528

Table 6. Environmental risks, opportunities and impacts

Risk (UOF)	Opportunity (UOF)	Profit (OOF)	Environmental impact (OOF)	Social impact (OOF)	Sustainability metric (OOF)
0.57071	0.11215	11,765,133,858	2,181,593,217	1,486,767,957	979,456,766
0.72134	0.47238	7,156,751,524	2,953,698,931	1,999,120,589	466,217,165
0.54237	0.37581	11,588,854,702	1,319,779,091	572,318,058	883,678,105

Based on (6)-(10), Table 7 explains the analysis of resource use and output efficiency in the optimization model. The ratio and IOF value are optimized; the result is a higher ratio (>1) in the first row, which indicates efficient resource use to achieve output. Conversely, lower ratios in the second and third rows indicate potential inefficiencies, and lower IOF values reflect more optimal decisions in resource use.

Table 7. Analysis of optimization of resource usage and output in IOF model

Row	Resource usage (IOF)	Expected output (IOF)	Ratio (expected output/resource usage)	$x_{k+1} - x_k$	IOF (optimized value)
1	1,354,299,579	2,389,228,439	1.763	0.08947	1.852
2	2,385,251,904	1,866,496,057	0.783	122.455	2.008
3	2,676,230,579	1,494,349,528	0.558	152.680	2.085

Table 8 provides important analysis on how risks, opportunities, and state changes are measured and optimized. By understanding the differences between risks and opportunities and the optimized UOF values, a larger difference (risk-opportunity) in the first row indicates a riskier scenario, with a higher UOF value indicating a less optimal decision. Lower UOF values (in the second and third rows) indicate better management of risks and opportunities, with more controlled system changes, resulting in more effective optimization. Table 9 describes the profit, environmental impact, social impact, and sustainability factors optimized in the financial prediction model. The optimized ratio, deviation, and OOF values help in understanding how well business decisions can deliver optimal financial results while maintaining sustainability and minimizing negative impacts, where higher ratios in the first and third rows indicate good financial results, while lower ratios in the second row indicate lower sustainability efficiency. Lower OOF (optimized value) (as in the third row) indicates that the model has achieved an optimal balance between profit, environmental impact, social impact, and sustainability.

Table 8. Uncertainty optimization analysis: risk, opportunity, and UOF value

Row	Risk (UOF)	Opportunity (UOF)	Difference (risk-opportunity)	$A_k x_k - x_{k+1}$	UOF (optimized value)
1	0.57071	0.11215	0.45856	0.94456	140.312
2	0.72134	0.47238	0.24896	0.64177	0.89073
3	0.54237	0.37581	0.16656	0.53240	0.69896

Table 9. Output optimization analysis: profit, environmental and social impact, and OOF value

Row	Profit (OOF)	Environmental impact (OOF)	Social impact (OOF)	Sustainability metric (OOF)	Ratio (profit - environmental - social/sustainability)	$Cx_k + Du_k - y_k$	OOF (optimized value)
1	11,765,133	2,181,593	1,486,767	979,456	8.084	105.632	914.032
2	7,156,751	2,953,698	1,999,120	466,217	4.625	0.75412	537.912
3	11,588,854	1,319,779	572,318	883,678	10.924	123.445	1.215

Table 10 contains the optimal parameters required to direct and manage the system in a MPK. Where the MPK value (261.284) is the result of optimization of the MPK. MPK combines several different optimization objectives, such as minimizing resource usage, reducing uncertainty, and maximizing output results based on (11). A lower MPK value is generally desirable because it indicates that the model has achieved an optimal balance between competing factors. By understanding the optimal value of each parameter, decision makers can better optimize strategies and actions to achieve desired outcomes, manage uncertainty, and maintain a balance between various objectives.

Table 10. Optimization results of state, control, and disturbance parameters with MPK values

Parameter	Optimal value
x_{k1}	0.0923
x_{k2}	-0.0394
x_{k3}	0.0151
u_{k1}	0.1958
u_{k2}	-0.0256
u_{k3}	0.0779
d_{k1}	-0.0941
d_{k2}	0.1710
d_{k3}	-0.0378
MPK value	261.284

Based on Table 10, an analysis of the MPK results was carried out by highlighting the model prediction accuracy and displaying the prediction error (residual) in the same 3D visualization, can be seen in Figure 2. 3D surface plot of predicted MPK values: high points on the surface (marked in yellow) indicate areas where the model predicts high MPK values, while low areas (marked in purple) indicate lower predicted values. These changes in values indicate that the model is quite responsive to changes in the input variables. The variation in MPK values is visible on the surface plot, with some peaks and valleys indicating significant changes in predictions. 3D scatter plot of predicted MPK with residuals, most of the points are in more neutral colours (light blue or pink), indicating that the model's predictions are generally quite accurate. This plot combines the predicted MPK with its residuals (the difference between the predicted and actual values). Contour plot of predicted MPK values looks at the pattern of how predicted MPK values change across the input range. The 2D contour shows the predicted MPK values across the input space. Contours with different colours indicate different levels of predicted values. 3D scatter plot of predicted MPK values with colour by value, clustering of colours shows patterns where higher or lower predictions lie. This can be used to understand the distribution of model prediction values and identify areas where higher or lower predictions tend to occur. This plot shows the MPK predictions with the colouring indicating the predicted value itself, showing the distribution of predicted values across the input space.

The fluctuations in the IOF, UOF, and OOF values indicate the complexity of the optimization process where multiple factors and objectives compete with each other. As the iterations increase, the values tend to stabilize and approach the point of convergence. This indicates that the optimization algorithm gradually finds a more balanced solution among multiple conflicting objectives. Figure 3 shows the iterative process of the optimization algorithm in achieving a Pareto-optimal solution, where no single objective can be further improved without sacrificing other objectives. This is particularly relevant in business decision-making under uncertainty where input efficiency, risk management, and output management must be balanced. This graph provides a visual representation of the multi-objective optimization process in a complexity prediction model. It illustrates how the values of the optimization functions (IOF, UOF, and OOF) and the combined MPK values fluctuate and converge during the iterations, indicating that the search for an optimal solution integrates multiple objectives.

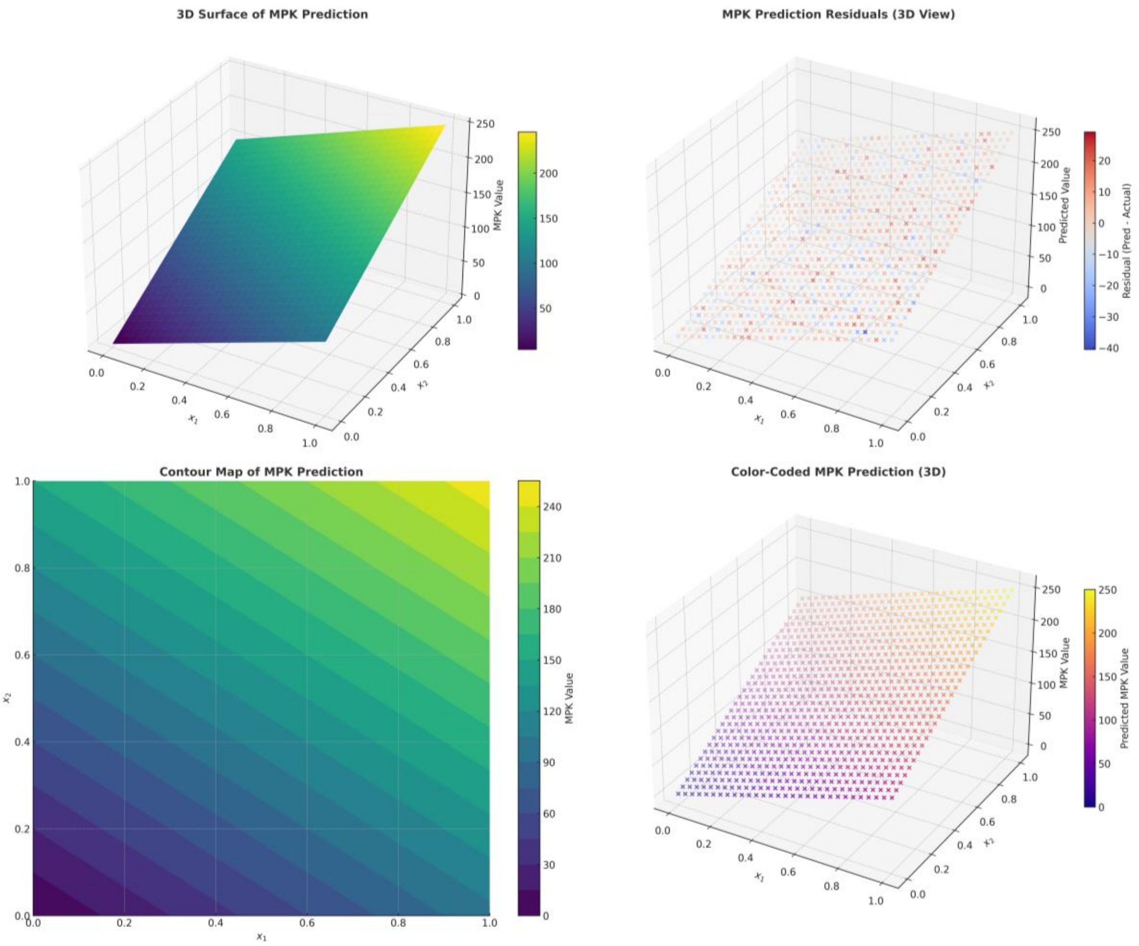

Figure 2. MPK prediction analysis: surface visualization and residual scatter

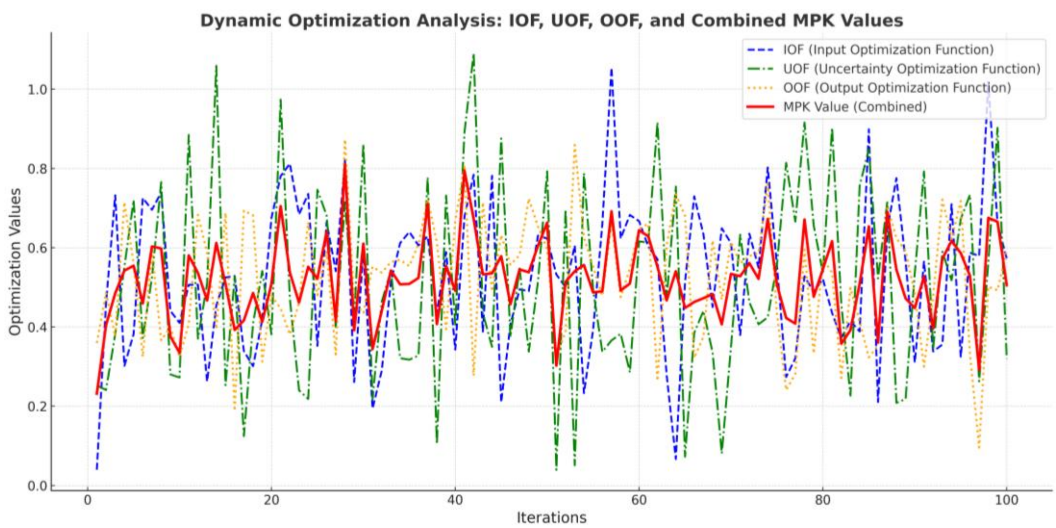

Figure 3. Dynamic optimization analysis of IOF, UOF, OOF, and combined MPK values

3.2. Model evaluation

The evaluation methods employed in this work include MSE, RMSE, MAE, and R^2 score. The MSE represents the mean square of the discrepancy between the expected values [25]. The RMSE is the square root of the MSE, resulting in an error that is equivalent in magnitude to the predicted variable [26], [27]. The MAE quantifies the average absolute discrepancy between anticipated values and the actual values [28]. The R^2 score quantifies the extent to which the predictor factors account for the variability in the target variable. The metric spans from 0 to 1, with larger values indicating a superior model [29].

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2 \tag{12}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2} \tag{13}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i| \tag{14}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i=1}^{n}(y_i - y)^2} \tag{15}$$

MSE measures the average of the squared differences between the predicted and actual values. An MSE of 20.112 indicates that the model is quite good at predicting the data, with most prediction errors being relatively small. RMSE is the square root of MSE and gives the prediction error in units equal to the variable. An RMSE of 2.267 indicates how far, on average, the model predictions differ from the actual values, indicating that the model predictions are very close to the actual values, meaning the model is performing well. MAE measures the average absolute error between the predicted and actual values. An MAE of 2.351 indicates that the model predictions are 2.351 units from the actual values, indicating good accuracy. R^2 score (coefficient of determination) measures the proportion of variance in the dependent variable that can be explained by the independent variables in the model. An R^2 of 0.884259 indicates that the model is able to explain about 88.4% of the variability in the output data, indicating that the model is performing very well. The high R^2 score value along with low MSE, RMSE, and MAE values indicate that this model has a very good ability to predict data. can be seen in the Table 11.

Table 11. Model evaluation

Metric	Value
MSE	20.112
RMSE	2.267
MAE	2.351
R^2 score	0.884259

4. CONCLUSION

Based on the results of the predictive model evaluation, it can be concluded that MPK shows good performance in predicting data with high complexity. This model successfully integrates IOF, UOF, and OOF to provide solutions in financial or business data analysis. The evaluation results show that the model has a MSE of 20.112, a RMSE of 2.267, and a MAE of 2.351, reflecting a high level of prediction accuracy with low error. An R^2 value of 0.884259 indicates that the model is able to explain approximately 88.4% of the variability in the data, confirming its ability to capture data patterns and associated complexity. Implementing MPK models improves predictive performance but also provides a multi-objective approach that allows users to manage risks, exploit opportunities, and optimize outcomes.

FUNDING INFORMATION

The authors would like to thank DPPM Kemdiktisaintek for the fundamental regular research with grant numbers 22/C3/DT.05.00/PL/2025, 7/SPK/LL1/AL.04.03/PL/2025, 76/P3MPI/3.1.1/VI/2025.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Mahyuddin Khairuddin Matyuso Nasution	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

To ensure fair and objective decision-making, the authors of this manuscript declare any associations that could potentially pose a conflict of interest, whether financial, personal, or professional. Non-financial competing interests include expressions of competing political, personal, religious, ideological, academic or intellectual interests. The authors hereby declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Therefore, the authors declare no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals involved in this study.

ETHICAL APPROVAL

Research relating to human use has complied with all relevant national regulations and institutional policies in accordance with the principles of the Declaration of Helsinki and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data supporting the findings of this study are available from the corresponding author on reasonable request. For further questions or data access, please contact the corresponding author.

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