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AUTOMATING CORRECTIVE ACTIONS AND OPTIMIZED SUBCONTRACTOR EVALUATION PROJECT

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ABOUT COMPANY

Aselsan, which was founded in 1975, is a major player on the global stage in addition to helping to strengthen Turkey's defense capabilities. Specializing in a wide range of high-tech solutions spanning multiple disciplines, such as defense electronics, communications, radar, electronic warfare, space technologies, and cybersecurity, Aselsan is one of Turkey's leading defense enterprises. Through the optimization of significant issues with subcontractor assessment and nonconformity management, this capstone design project seeks to improve these procedures within the Production and Supply Quality Management Directorate of Aselsan.

Figure 1. Products of Aselsan

CURRENT SYSTEM

Current System for Z7 Notifications at Aselsan

Incoming product batches are examined in detail during Aselsan's production and quality control processes. This first stage is critical to ensure that products meet high standards. Products are approved by quality control engineers and sent for further processing or final shipment. During quality control, abnormalities are reported by technicians, and this information is updated regularly. The information held in the system is reviewed regularly and when significant problems are detected, the Z7 Corrective Action Process is initiated. This process includes root cause analysis using the 8D analysis method.

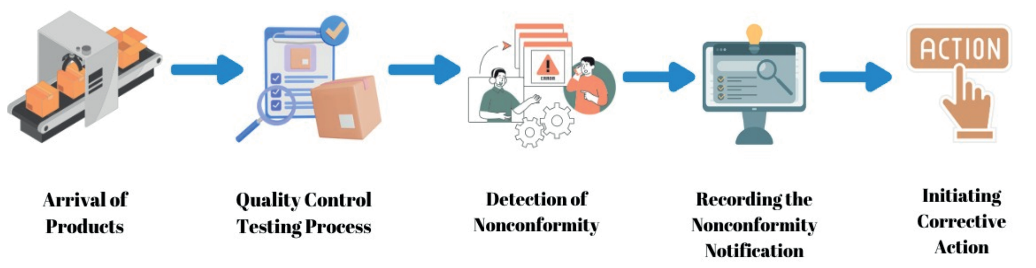

Figure 2. Current Process of Z7

Subcontractor Evaluation System at Aselsan

Aselsan uses a detailed subcontractor evaluation system that focuses on multiple key criteria to ensure quality and reliability. This process includes assessing technical capabilities to meet complex product requirements and financial stability to maintain long-term contracts. Additionally, sustainability and compliance with business ethics are also very important. Successful subcontractors who meet these stringent standards strengthen long-term partnerships by signing Strategic Collaboration Agreements. These subcontractors, examined by Aselsan's expert commission, must demonstrate consistently high performance, including receiving at least 80 points on delivery and quality measures in at least two of the last five years.

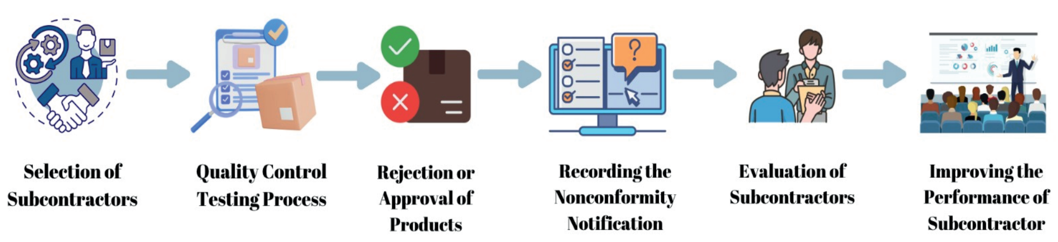

Figure 3. Current Process of Subcontractor Evaluation System

PROBLEM DEFINITION

Problem Definition for Automating Corrective Actions

Aselsan's Quality and Control Department currently relies on manual and subjective methods to make decisions about corrective actions for issues in final products. This manual approach can lead to time losses, delayed responses to recurring errors, and oversight due to the large volume of data, impacting both production and overall operations.

Problem Definition for Subcontractor Evaluation

Aselsan faces challenges due to the lack of automated processes for assessing product-supplying subcontractors. This issue leads to difficulties in managing large volumes of data and time constraints, complicating quality control and hindering supply chain improvements. The absence of automated evaluation processes can impact Aselsan's overall effectiveness and adherence to quality and reliability standards. To address these issues, it is crucial to implement automated decision-making tools, enhance data management systems, and establish stringent procedures for dealing with non-compliant subcontractors.

The project aims to reduce nonconformity recurrence and operational costs by automating and refining Z7 corrective actions and subcontractor assessments, using advanced technology to enhance process accuracy and efficiency, while also standardizing evaluation procedures to ensure all subcontractors meet quality and reliability standards, thus optimizing production and maintaining high quality.

METHODOLOGY

Data Set

Our dataset from Aselsan's production and supply logs tracks key metrics like Notification Items, Scrap Cost, and Rework Labor Cost, highlighting high efficiency with minimal error rates and waste. Most values cluster near zero, indicating effective quality control and cost management in production processes. This data underlines Aselsan's capability in maintaining high production standards and operational excellence.

	Total Amount of Data	Total Amount of Opened Z7
Production Dataset	10450	425
Supply Dataset	7198	117
Whole Datasets	17648	542

Table 1. Dataset Information Table

Imbalanced data occurs when one class significantly outnumbers another in a dataset, causing biases in machine learning models. This is seen in Aselsan's data, where routine operations vastly outnumber corrective actions. To address this, techniques like resampling and specialized algorithms are used to improve model accuracy for the underrepresented class, ensuring better management of critical but infrequent events.

Automating Z7 Corrective Action: An Overview of Applied Methodologies

In our project aimed at automating Z7 corrective actions at Aselsan, we employed a diverse array of sampling techniques and machine learning models to handle data imbalances and enhance prediction accuracy. Our approach included under-sampling methods like Instance Hardness Threshold, Tomek Links, Near Miss, AllKNN, Random Under Sampler, and Edited Nearest Neighbours (ENN); over-sampling techniques such as SMOTE, Borderline-SMOTE, and KMeans SMOTE; and mixed methods like SMOTEENN and SMOTETomek. For model development, we utilized algorithms tailored for imbalanced data, including Logistic Regression, Support Vector Machine, Random Forest, XGBoost, and notably, the Balanced Bagging Classifier. This classifier, which adjusts training by creating balanced subsets from the majority class, emerged as the most effective, particularly when supplemented with hard negative mining and a sliding window method to ensure continuous learning and minimize overfitting. These methodologies collectively enhanced our ability to predict and manage Z7 corrective actions, significantly boosting the reliability and operational efficiency of Aselsan's production processes.

	Balanced RandomForest Classifier	BalancedBagging Classifier	RUSBoost Classifier	EasyEnsemble Classifier	Random ForestClassifier	LogisticRegression	XGBClassifier	SVM
None	0,00	0,00	0,00	0,00	1,48	1,32	1,51	1,10
AllKNN	1,82	0,00	1,77	1,75	1,60	1,56	1,54	1,00
TomekLinks	1,78	1,79	1,77	1,71	1,60	1,44	1,54	1,00
Random Under Sampler	1,81	1,79	1,77	1,72	1,80	1,74	1,81	1,43
NearMiss	1,74	1,12	1,12	1,13	1,60	1,70	1,70	1,09
Edited Nearest Neighbours	1,84	1,82	1,77	1,77	1,56	1,56	1,59	1,00
Neighbourhood Cleaning Rule	1,76	1,85	1,77	1,70	1,56	1,53	1,65	1,00
Instance Hardness Threshold	1,83	1,85	1,77	1,80	1,69	1,66	1,66	1,00
Borderline SMOTE	1,56	1,54	1,68	1,70	1,45	1,71	1,62	1,65
SMOTE	1,63	1,66	1,48	1,66	1,63	1,70	1,63	1,66
ADASYN	1,60	1,60	1,52	1,63	1,60	1,71	1,61	1,50
SMOTEN	1,56	1,50	1,31	1,62	1,45	1,56	1,63	1,63
KMeansSMOTE	1,54	1,47	1,43	1,49	1,51	1,44	1,63	1,12
SMOTEENN	1,39	1,54	1,73	1,70	1,69	1,67	1,76	1,74
SMOTETomek	1,50	1,63	1,73	1,70	1,69	1,67	1,76	1,74

Table 2. Analysis of Recall Results for Categories 1 and 0 in Summation

Further refinements were made through hard negative mining, focusing on the misclassified predictions to improve accuracy, and a sliding window method to ensure continuous learning and avoid overfitting. The balanced Bagging model, enhanced through these strategies, proved highly successful in predicting Z7 corrective actions, thus improving operational efficiency and predictive accuracy in our processes.

Subcontractor Evaluation Methods

In our project, we leveraged the Multi-Attribute Utility Theory (MAUT) and the TOPSIS methodology to optimize subcontractor selection for Aselsan. MAUT, used for its effectiveness in complex decision scenarios, involves maximizing a utility function and employing the Swing Weight method for criterion weighting. This approach normalizes data on a 0 to 1 scale for comparative analysis, enhancing decision-making precision by clearly delineating priorities and differences between criteria. Conversely, TOPSIS evaluates subcontractors by comparing them to ideal solutions, enabling a systematic assessment across multiple criteria. This method normalizes data, applies predetermined weights, and calculates the relative proximity to ideal solutions, ranking subcontractors based on their performance metrics. These methodologies, implemented via Python, utilize libraries like Pandas for data manipulation and NumPy for numerical operations, facilitating an objective, efficient evaluation of subcontractor performance across different product categories. This comprehensive approach not only streamlines the decision-making process but also supports Aselsan's strategic objectives in quality management and supply chain optimization.

Figure 4. Criteria of MAUT and TOPSIS Method

RESULT

	Predicted Negative	Predicted Positive
True Negative	3401	24
True Positive	15	90

		Precision	Recall	F1-score	Support
Category Class	0	1.00	0.99	0.99	3425
	1	0.79	0.86	0.82	105
Scores	accuracy			0.99	3530
	macro avg	0.89	0.93	0.91	3530
	weighted avg	0.99	0.99	0.99	3530

Table 3. Results of the Balanced Bagging Classifier and Instance Hardness Threshold Sampling Methods

The Balanced Bagging model coupled with Instance Hardness Threshold Sampling has demonstrated exceptional performance in our project, achieving a remarkable accuracy of 99%. The model exhibits high precision (1.00) and recall (0.99) for the majority class (Class 0) with an F1-score of 0.99, indicating nearly perfect classification. For the minority class (Class 1), while the precision is slightly lower at 0.79, the recall is impressive at 0.86, with an F1-score of 0.82, showcasing strong capability in identifying true positive instances effectively. The confusion matrix further corroborates the model's efficacy with 3401 true negatives and 90 true positives, confirming the model's robustness in handling imbalanced data. This high performance underscores the model's utility in critical decision-making scenarios, ensuring reliable and accurate predictions critical for operational efficiency and quality control processes.

TOPSIS Results			MAUT Results		
Firms	Score	Rank	Firms	Score	Rank
211495	0,97378	1	211495	0,982193	1
710230	0,967321	2	210365	0,980174	2
210043	0,959302	3	117045	0,972182	3
117045	0,954699	4	210546	0,946284	4
210365	0,953503	5	710230	0,944824	5
210546	0,906482	6	117567	0,942036	6
117567	0,906353	7	210043	0,936606	7
112155	0,885207	8	210712	0,919737	8
210712	0,860703	9	112155	0,913485	9
510270	0,846038	10	210050	0,908671	10

Table 4. Result of MAUT and TOPSIS Method

In our evaluation using TOPSIS and MAUT methodologies, company 211495 consistently ranked first for Product Type 1 across both methods, achieving high performance scores. This type of results analysis has been conducted for every product type. The consistency across methodologies confirms their reliability in subcontractor performance assessment. The rankings of the top 10 subcontractors for each product type show minor variations, validating both methods' effectiveness in supporting strategic decision-making in supply chain management.

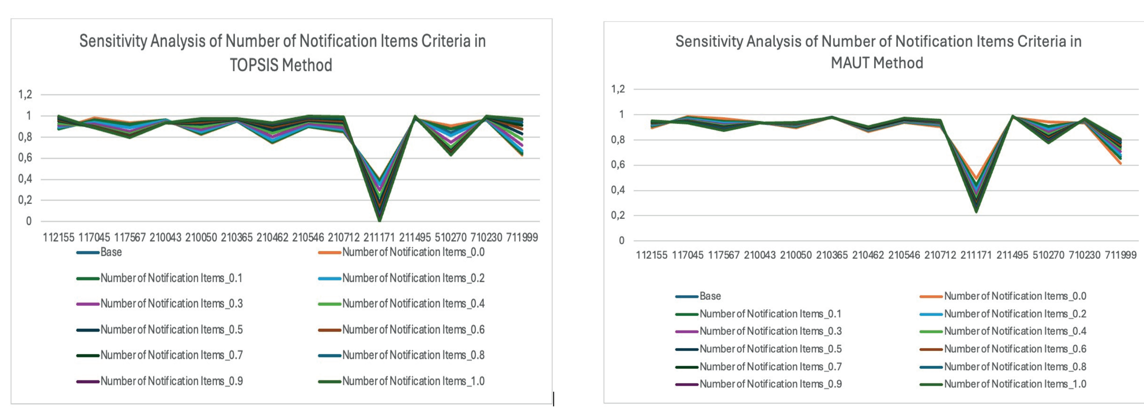

Figure 5. Result of MAUT and TOPSIS Sensitivity

In our subcontractor evaluation sensitivity analysis using MAUT and TOPSIS, we examined how changes in weighting criteria affect rankings. This analysis highlights how robust our results are under varying conditions. Specifically, adjusting the weight of the Number of Notification Items for Product Type 1 showed little impact on overall rankings in both methodologies, confirming that this criterion does not significantly influence subcontractor performance evaluations. Such analyses help ensure the reliability of our evaluation process and support strategic decision-making by identifying stable performance factors.

CONCLUSION

The project significantly enhanced Aselsan's operational efficiency by automating production and quality control processes, particularly Z7 corrective actions and subcontractor evaluations. Automation reduced engineering review time dramatically, leading to substantial cost savings. For example, earlier detection of defects in specific stock numbers demonstrated potential savings, highlighting automation's impact in reducing losses due to defective materials and process errors. The integration of MAUT and TOPSIS methodologies using Python tools like NumPy and Pandas streamlined subcontractor evaluations, ensuring consistent quality and supporting strategic supply chain management decisions. This approach improved efficiency, reduced errors, and enhanced cost-effectiveness across Aselsan's operations.

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