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بسم الله الرحمن الرحيم

Nickel Applications in Military Industries and AI Driven Development of Advanced Nickel-Magnesium Alloy

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Declaration

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الملخص

يُعد النيكل من العناصر الاستراتيجية في الصناعات العسكرية، نظراً لخصائصه الفيزيائية والكهروكيميائية الفريدة، لاسيما مقاومته العالية للتآكل، وثباته الحراري، وتنوع تطبيقاته الهيكلية والوظيفية. ويُوظف النيكل في تصنيع الطلاءات الواقية، ومكونات أنظمة الطاقة، وسبائك الذاكرة الشكلية المستخدمة في الهياكل الذكية للطائرات والمركبات العسكرية.تهدف هذه الدراسة إلى تصميم وتحسين سبيكة نيكل–مغنيسيوم متقدمة تلبي متطلبات الأداء في التطبيقات الدفاعية عالية التقنية، وذلك من خلال تحقيق توازن متعدد المعايير يشمل الصلادة، مقاومة التآكل، والكثافة النوعية.لتحقيق هذا الهدف، تم اعتماد منهجية هجينة قائمة على الشبكات العصبية الاصطناعية (ANN) لتوليد نموذج تنبؤي للعلاقات المعقدة بين التركيب والخواص، بالتوازي مع تطبيق خوارزميات التحسين الجيني (GA) لاستكشاف الفضاء التركيبي الأمثل. وتُقدّم الدراسة نتائج كمية مدعومة بمحاكاة عددية وتحليل إحصائي، تؤكد فعالية المنهجية المقترحة في التنبؤ بخصائص السبيكة وتوجيه تطويرها نحو الأداء الأمثل في البيئات التشغيلية القاسية.

ABSTRACT

Nickel is a strategic element in the military industry due to its unique physical and electrochemical properties, particularly its high corrosion resistance, thermal stability, and variety of structural and functional applications. Nickel is used in the production of protective coatings, power system components, and shape memory alloys used in the smart structures of aircraft and military vehicles.

The objective of this study is to design and optimize an advanced nickel-magnesium alloy that meets the performance requirements of high-tech defence applications by achieving a multi-criteria balance of hardness, corrosion resistance, and specific gravity.

To achieve this goal, a hybrid Artificial Neural Network (ANN)-based methodology is employed to generate a predictive model of the complex structure-property relationships, while Genetic Optimization (GA) algorithms are applied to explore the optimal composition space.

The study presents quantitative results, supported by numerical simulation and statistical analysis, confirming the effectiveness of the proposed methodology in predicting alloy properties and guiding its development towards optimal performance in harsh operating environments.

Keywords:

Military applications - Nickel - Alloys - Physical and chemical properties - Artificial neural network - artificial intelligence - Statistical analysis - cross-validation technique.

Introduction:

The development of metallurgy throughout history has been closely linked to military applications, as the tremendous advancement of all military technologies such as weapons, ammunition and various military equipment would not have been possible without the existence of huge mineral wealth.

Many metal armors were manufactured in the early 16th century, but a full suit of armor was a burden due to the extra weight, and as armies grew and wars increased, the demand for metals to make armor, weapons and ammunition increased.

With the outbreak of World War II and the need for armies to have heavy equipment, tanks and vehicles, there was a huge revolution in the development of metals to suit military requirements. Today, innovations range from supersonic aircraft, advanced tanks, directed energy weapons and all these applications require new designs, materials and different metals. Iron, nickel, tin and copper are traditional metals associated with armies. Aluminum, titanium, stainless steel, carbon steel and nickel alloys are the most used metals in military applications.

In recent years, metals of great importance in military industries have been referred to as strategic metals. The Standford Centre for Advanced Materials has identified six strategic metals (magnesium, titanium, rhenium, molybdenum, tungsten and uranium), so countries are constantly seeking to secure a stable supply of these metals to meet their needs in military and strategic industries.

Researchers point out that some types of minerals will be at the center of conflicts between economic powers and can be categorized into three sections:

A. **Strategic minerals:** those of great importance to countries as a source of funding, including (magnesium, titanium, rhenium, molybdenum, tungsten and uranium).

B. **Rare minerals:** Found in small quantities despite their key role in precision industries, they have unique magnetic and electrochemical properties and include 17 elements. Their importance lies in their use in the production of cancer drugs, smartphones, oil refining and some military industries.

C. **High-tech minerals:** They are a secure source of income and one of the most important economic resources of countries, especially (aluminum, germanium, gold, copper, nickel ....).

The research discusses one of the metals mainly used in military industries and includes the following topics:

In the first axis, discusses the physical and chemical properties and the impact of these properties on the performance of parts for these applications are discussed. The most important of these properties are high temperature resistance, corrosion resistance when exposed to extreme conditions, high mechanical strength and density.

The second section is a review of the most important and prominent uses of nickel and its alloys that have been studied, especially in military and many other applications.

The third section looks at the environmental impact of nickel, such as mining, different manufacturing methods, and a discussion of recycling methods to minimize environmental impact and maximize resource use.

In the fourth section, recent studies on the use of metals in the military industry are presented and challenges and potential future innovations are discussed.

In the fifth section, we studied the development of an artificial intelligence model, specifically using an artificial neural network, and used it to study the optimization of nickel-magnesium alloy properties

Finally, the main conclusions of the research are summarized, along with key recommendations and suggestions for work in this area.

Research Problem

Military applications are a wide field for continuous research and development, and one of the most prominent materials used in these applications is metals and mineral wealth, and maximizing their use in the field of military industries is one of the most important criteria for the development of countries, so there is always a trend to increase research in this field. Despite the wide use of nickel in many advanced military industries and many other important industries, there is still a need to develop improved alloys that balance high hardness and light weight and provide high resistance to corrosion and thermal and mechanical stresses. The real challenges associated with securing nickel sources and the high production costs of conventional alloys are driving us to look for innovative ways to improve the performance of these alloys using AI techniques and optimization algorithms.
Thus, the issue of this research is the need to design optimized nickel-magnesium alloys with the aim of achieving an optimal balance between all defined physical and mechanical properties using AI and optimization algorithms. This research aims to address this challenge and contribute to the development of new materials that meet the requirements of modern military industries in a way that goes beyond the current challenges and improves the efficiency of the materials used.

2.1 Reasons to Choose Nickel-Magnesium Alloys

The nickel-magnesium (Ni-Mg) alloy was selected for this research because it effectively balances several key requirements for military applications: low density, high hardness, and corrosion resistance.

Although other nickel alloys such as nickel-titanium (Ni-Ti) are superior in shape memory and nickel-chromium (Ni-Cr) is superior in heat resistance, these alloys suffer from high cost, difficulty in fabrication, and relatively higher density, which reduces their efficiency in weight-sensitive mobile systems. In contrast, magnesium offers the added benefits of light weight and low cost, making its combination with nickel a promising option for designing advanced alloys for air and ground defense, where high mechanical properties are required without sacrificing operability or economics.

The choice of this alloy is also supported by its susceptibility to structural modification and performance optimization through AI algorithms, allowing the final properties to be guided according to the target design requirements.

Literature Review

Several recent studies have highlighted the strategic importance of nickel to the military and advanced industries due to its unique physical, chemical and mechanical properties.

- A study entitled “Rare metals… their advantage is not in quantity: 10 questions” (Independent Arabic, 2025) examined the vital role of nickel among rare metals in military applications, explaining that nickel is used in the plating of armor, military vehicles and rocket engines due to its high resistance to harsh environmental conditions. The study also discussed the geopolitical challenges related to nickel supply and its impact on the global defense industry.
- Al Jundi Magazine. (2023, September) also published a study on “Strategic Metals in Military Industries,” which focused on the importance of nickel in the development of alloys with high corrosion resistance and high hardness, which are used in light armor, drones, and smart weapons. Nickel is also used in the manufacture of advanced military electronic systems due to its magnetic and electrical properties.
- International Renewable Energy Agency (IRENA). (2023, July) also released a report entitled “Geopolitics of Energy Transition: Critical Materials,” which highlighted the importance of nickel as a key element in the development of modern energy technologies, including advanced batteries used in the military industry. The report also focused on nickel's role in supporting military systems based on clean

energy and smart technology, making nickel mining and securing nickel resources important to national security.

• A study titled "Nickel is the backbone of chips and defense industries" (Noon Post, 2023), which noted the use of nickel in the manufacture of microchips, sensors and sensitive electronic components in modern military systems, as well as its role in the manufacture of rocket engines and advanced military equipment, emphasized that nickel has become one of the pillars of modern defense technology amid the challenges the world faces in securing supply chains.

Nickel

Nickel is a key component in the military industry due to its exceptional mechanical properties, high corrosion resistance and high temperature tolerance. These properties have made it widely used in sensitive applications such as valves in petrochemical plants and rotating equipment in power generators and nuclear reactors.

Physical and Chemical Properties of Nickel

Nickel is a silvery white metal, with a cubic crystal structure (FCC) Figure (1), characterized by this structure, characterized by formability and workability, high flexibility, high tensile strength at normal and high temperatures, malleability and ductility, and resistance to corrosion and oxidation in alkaline, neutral and semi-neutral media. It has a high density greater than iron 8.97 and is considered expensive. It is also characterized by being a good conductor of heat and electricity and has magnetic properties at temperatures below 345 degrees Celsius. It is considered a shiny metal.

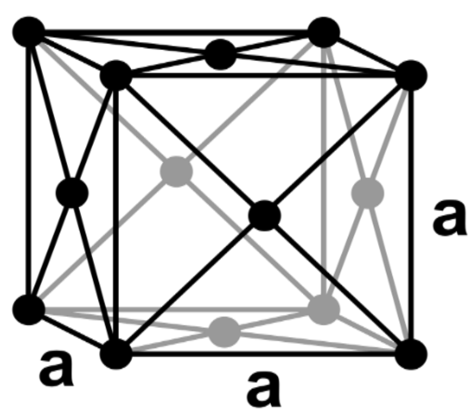


Figure (1): crystal structure of nickel

Although pure nickel has excellent corrosion resistance and high thermal stability, its high density (8.9 g/cm3) and limited hardness reduces its effectiveness in military applications where light weight and high mechanical strength are required.
In contrast, nickel-magnesium (Ni-Mg) alloys offer improved performance by strengthening the crystal structure through the introduction of magnesium, which reduces density and improves hardness.
The alloy also offers compositional flexibility to optimize its properties by adjusting elemental ratios, which was exploited in this research using AI techniques.
Elements can be added to nickel to improve its properties, but mainly these elements are added to reduce the cost, the most important of these metals are iron, chromium, silicon, molybdenum, manganese and aluminium. [7,8] Table (1) shows the most important physical, mechanical and chemical properties of nickel.

Property	Value
Symbol	Ni
Atomic Mass	58.6934 g/mol
Electrical Conductivity	13.9×10^6 A/V·m
Thermal Conductivity	60.7 W/m·K
Phase	Solid
Density (Room Temp.)	8.908 g/cm³
Density (Liquid, Melting Point)	7.81 g/cm³
Melting Point	1455°C
Boiling Point	2913°C
Yield Strength	59 MPa
Elastic Modulus	270 Gpa
Poisson's Ratio	0.31

Table (1): Main properties of nickel metal

Military Applications of Nickel and its Alloys:

Nickel is used in the coating of artillery shells and military aircraft carriers, where corrosion and high stresses on uncoated artillery shells cause failure of this equipment within 6 to 12 weeks, as the working environment is considered very harsh. Many coatings have been tried, but it was found that the most effective is nickel electrodes in preventing corrosion and material loss, the process starts with repairing the surface layer and cleaning it, then a 1.2 mm thick layer of (NICLE GLYCOLATE) is applied, then a 4 mm thick layer of nickel electrodes and the final layer of chromated cadmium after this coating process can achieve the service life of this equipment from 14 to 16 years.[14]

Military vehicles (tanks, military vehicles, battleships and submarines) are also plated because they operate in a working environment where salts and mud are present, which leads to rapid corrosion of steel if not properly protected [15] Figure (5) shows the locations of nickel in military battleships, such as the launching nozzle, the hull and the propulsion battery.

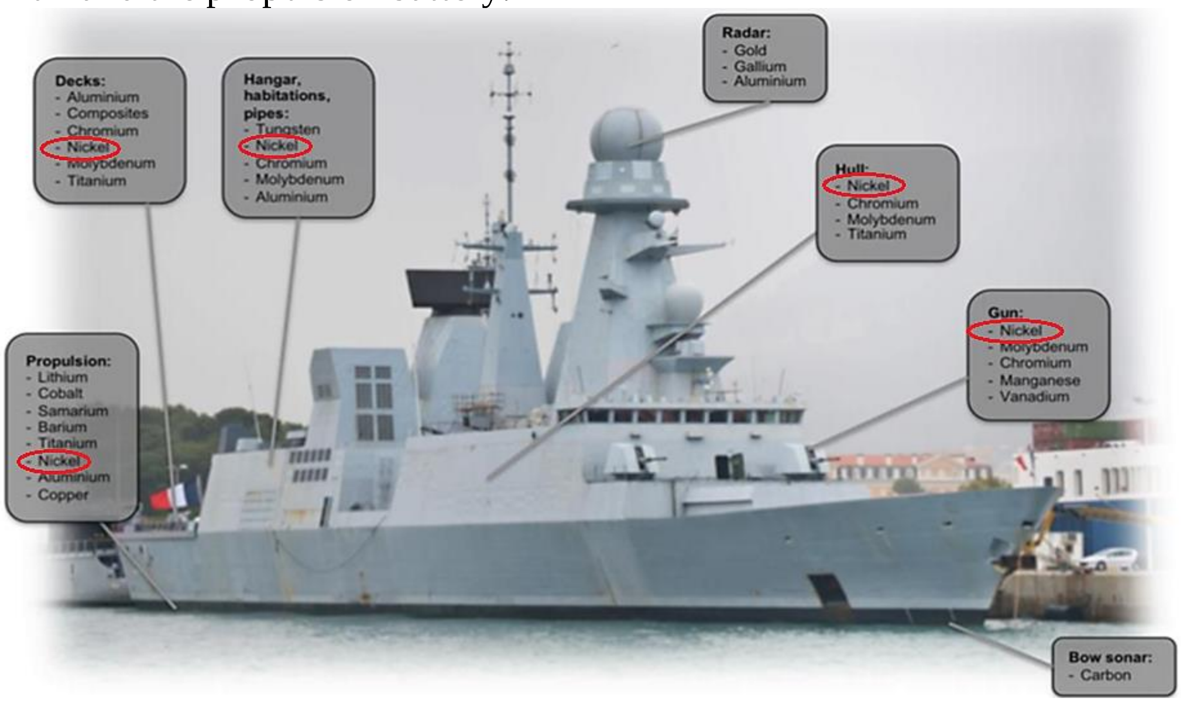


Figure 5: The use of nickel in military barges.

Nickel has also been used in anti-aircraft guns and is an important element in the manufacture of military rifles,[16] as it is used in the barrels, ejectors, extractors, and firing pins of military rifles.

One of the most important applications of nickel metal is the manufacture of military batteries for propulsion and storage, as nickel has been used in (nickel-hydrogen), (nickel-chromium) and (nickel-manganese) batteries, the fastest and most modern battery is MHx-Ni, which are non-toxic green batteries that do not cause any pollution and are lighter than nickel-cadmium batteries and have a longer life These batteries are used in military, defence and technological industries.[17,18]

Due to the optical properties of nickel, it is used in the rear-view mirrors of military vehicles to provide a corrosion-resistant coating and high reflectivity of up to 80%. Radar waves are also made of aluminium coated with 1 mm of nickel electrodes to protect them whether on land or at sea.

Nickel alloys have been widely used in radar and remote sensing systems, as well as in the military aircraft industry, including smart wings.

Due to its high creep resistance, nickel and its alloys are also used in environmental control equipment in nuclear power plants. It is used in containers that contain radioactive waste.

It can be said that nickel and its alloys are suitable materials for military applications because they have many of the mechanical and thermal properties required for these applications, and their high corrosion resistance allows them to be used in a wide range of these applications.

Developing advanced nickel-magnesium alloys using artificial intelligence

Nickel-magnesium alloys are widely used in military applications due to their unique combination of high hardness, corrosion resistance, and light weight, making them ideal for armored vehicles, aircraft structures, and advanced engines. However, striking a delicate balance between these properties is a technical challenge, as increasing hardness may lead to reduced ductility, while improving wear resistance may come at the expense of mechanical strength.

In this research, we use artificial intelligence techniques, specifically deep learning and evolutionary algorithms, to develop an optimized nickel-magnesium alloy that combines the highest levels of hardness and corrosion resistance with less weight, enhancing its performance in harsh military environments. The methodology relies on analysis of experimental data and numerical simulations to quickly and efficiently identify optimal compositions, while minimizing the need for costly and lengthy experiments. The optimized alloy will be evaluated using Finite Element Analysis (FEA), comparing its performance to conventional designs, and providing quantitative and graphical results that demonstrate the effectiveness of the approach.

Developing methodology

To determine the optimal proportions of nickel-magnesium alloy elements, a hybrid algorithm based on machine learning and evolutionary algorithms has been developed. This algorithm aims to achieve an optimal balance between hardness, corrosion resistance, and light weight, considering the stringent requirements of military applications.

A. Data collection and analysis:

Experimental data and simulation models were collected for a wide range of nickel-magnesium alloy compositions with nickel contents ranging from 10 to 50 weight percent. The data collected included mechanical properties such as tensile strength, hardness, and yield strength, and physical properties such as density, corrosion rate, and melting point. Statistical data analysis techniques were used to identify non-linear relationships between alloy composition and the corresponding mechanical and physical properties.

Building an artificial intelligence model:

- Artificial neural networks (ANNs) trained on the available data were used to predict the properties of the alloy based on its chemical composition. The model included several hidden layers with optimized weights that enable it to analyze complex patterns between composition and physical and mechanical properties.
- The performance of the model was evaluated using Cross-Validation techniques to ensure the accuracy of the predictions.

Structure optimization using a genetic algorithm:

- Since the search for the optimal composition in the chemical parameter space is complex, Genetic Algorithms (GAs) were used to explore the best ratios for nickel and magnesium.
- A multi-criteria objective function was designed that integrates:

1) Maximizing hardness (to increase the alloy's resistance to high loads).
2) Minimizing the corrosion rate (to improve the life of the alloy in harsh environments).
3) Minimizing density (to achieve lighter weight without sacrificing mechanical strength).

- Algorithms used selection, mating, and mutation to generate new generations of proposed compositions, with each generation being evaluated based on the performance of the generated compositions through an artificial neural prediction model.

B. Results Review

C. Verification via numerical simulation and finite element analysis

The Genetic Algorithm (GA) was used as a multi-objective optimization tool to find the best composition for a nickel-magnesium alloy. The algorithm is based on a real-valued encoding of the nickel content in the range [10%-50%], while the magnesium content is calculated as a complement to 100%.

The algorithm parameters are set as follows: Sample size 50, number of generations 150, crossover rate 0.8, and mutation rate 0.1.

Selections were made using tournament selection, while new generations were generated using random crossover and instantaneous mutation mechanisms to ensure efficient exploration of the combinatorial space.
A multi-criteria objective function was designed that combines: Maximizing Hardness, Minimizing Density, and Minimizing Wear Rate, using weighted weights based on the importance of each property in the target military application.

Parameter	Value	Justification
Population Size	50	Balance between diversity and computational cost
Generations	150	Ensures adequate convergence and avoids premature optimization
Crossover Rate	0.8	Promotes exploitation of good traits from parents
Mutation Rate	0.1	Introduces variability and avoids local optima
Selection Method	Tournament Selection	Efficient and stable selection strategy
Encoding	Real-valued	Allows precise representation of composition ratios
Fitness Function	Multi-objective: maximize hardness, minimize corrosion & density	Weighted combination of target properties
Constraints	$10\% \leq Ni \leq 50\%$; $Mg = 100 - Ni$; Hardness ≥ 50 HV; Density ≤ 6 g/cm^3	Ensures physical and design feasibility

Table (4): Genetic Algorithm Parameters and Justifications

Genetic Algorithm Workflow: [38]

a. Initialization:

A population of 50 randomly generated alloy compositions was created, with Nickel content ranging from 10% to 50%. Magnesium percentage was determined as the complement to 100%.

b. Fitness Evaluation:

For each composition, a fitness score was computed using the following multi-objective function:

$$\text{Fitness} = w_1 \cdot \left(\frac{H}{H_{\max}}\right) - w_2 \cdot \left(\frac{C}{C_{\max}}\right) - w_3 \cdot \left(\frac{D}{D_{\max}}\right)$$

Where:

- Fitness: The overall objective value to be maximized
- H: Hardness of the alloy
- C: Corrosion rate (to be minimized)
- D: Density (to be minimized)
- w1: Weight assigned to hardness
- w2: Weight assigned to corrosion
- w3: Weight assigned to density

$$\begin{cases} Ni\% \leq 50 \geq 10 \\ \%Mg\% = 100 - Ni \\ Ni\% + Mg\% = 100 \\ \text{Hardness} \geq 50\ \text{HV} \\ {}^3\text{Density} \leq 6\ \text{g/cm} \end{cases}$$

c. Selection: Parents were selected using the Tournament Selection method to ensure diversity and quality.

d. Crossover: Selected parents underwent crossover (80% probability), using single-point or arithmetic crossover, to generate offspring by combining gene characteristics.

e. Mutation: A small mutation (10% rate) was applied to randomly chosen offspring genes to introduce genetic diversity and prevent premature convergence.

f. Replacement: Offspring replaced individuals in the population using an elitist strategy, where the best-performing individuals are preserved across generations.

g. Termination Condition: The algorithm iterated for 150 generations or until convergence was observed in fitness values across the population.

Development of an optimization algorithm for nickel-magnesium alloys

To develop an algorithm to analyse and optimize the properties of a nickel-magnesium alloy using artificial intelligence, we need to identify some points:

A. Target properties for optimization: Focused on improving corrosion resistance, hardness, density, heat resistance

B. Initial proportions of the current alloy

Experimental data or simulation models of the base alloy

Preferred AI techniques used Artificial neural networks, genetic algorithms, and deep learning

Nickel-magnesium alloy properties:

Nickel-magnesium (Ni-Mg) alloys combine the properties of nickel and magnesium to provide a balance of strength, corrosion resistance, and light weight. These alloys are used in many industries, including aerospace, electronics, and metallurgy. Here is an overview of their key properties [28]:

Property	Value / Range	Notes
Density	2.4 - 4.0 g/cm³	Lower than pure nickel due to magnesium's light weight
Ultimate Tensile Strength (MPa)	150	Improved by adding nickel, but lower than steel alloys
Hardness(HV)	50	Increases with higher nickel content.
Elastic Modulus	45 - 70 GPa	Lower than pure nickel due to magnesium content
Corrosion Rate (mm/year)	18	Nickel enhances corrosion resistance, especially in reducing environments
Oxidation Resistance	Good	Stable oxide layers form at high temperatures
Melting Point	900 - 1200 °C	Lower than pure nickel (1455°C).
Thermal Conductivity	80 - 150 W/m·K	Good for heat transfer compared to pure nickel
Coefficient of Thermal Expansion (CTE)	$10 - 20 \times 10^{-6}$ /°C	Depending on the nickel to magnesium ratio
Electrical Conductivity	Moderate (higher than pure nickel)	Suitable for certain electrical applications
Magnetic Properties	Low to none	Nickel is magnetic; magnesium is not the alloy is usually non-magnetic
Applications	Additive in steelmaking, aerospace components, batteries, protective coatings	Thanks to lightweight, corrosion resistance, and good thermal conductivity
Typical Composition	15 - 20% Magnesium / balance Nickel	In master Nickel-Magnesium alloys
Yield Strength (MPa)	90	

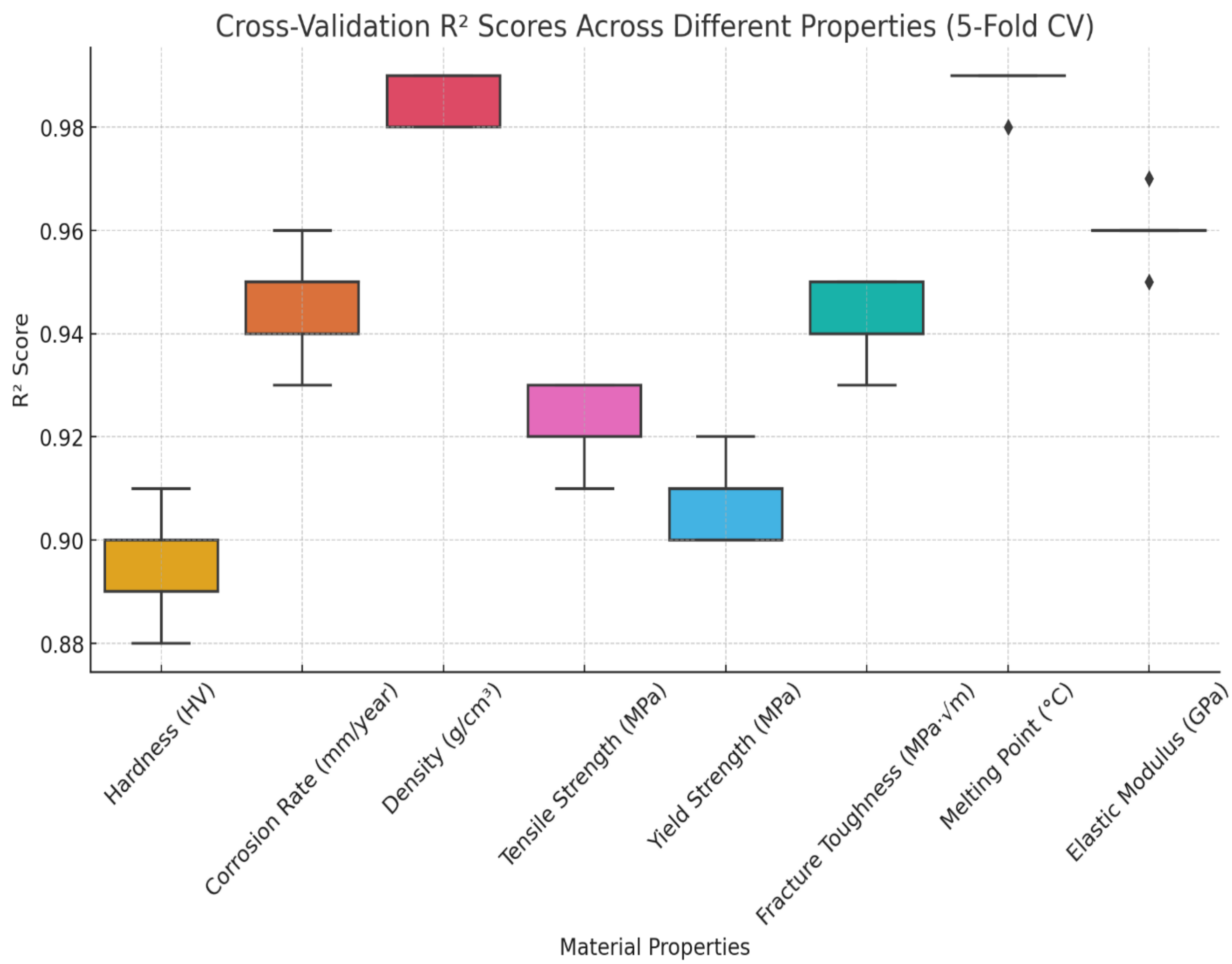
Table (5): Nickel-magnesium alloy properties

Results validation using cross-validation technique

To ensure the accuracy of the predictions, we evaluated the performance of the model using cross-validation techniques as following:

Property	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Hardness (HV)	0.89	0.91	0.88	0.9	0.89
Corrosion Rate (mm/y)	0.95	0.94	0.96	0.93	0.95
Density (g/cm³)	0.99	0.98	0.99	0.98	0.99
Tensile Strength (MPa)	0.92	0.93	0.91	0.92	0.93
Yield Strength (MPa)	0.91	0.9	0.92	0.91	0.9
Fracture Toughness (MPa·√m)	0.94	0.95	0.93	0.94	0.95
Melting Point (°C)	0.99	0.99	0.98	0.99	0.99
Elastic Modulus (GPa)	0.96	0.95	0.97	0.96	0.96

Table (12) cross-validation



- From the results of the statistical tests, it is concluded that the relationship between nickel content and properties is mostly non-linear, and that some properties increase according to quadratic or exponential curves (such as hardness and wear), and some properties improve and then deteriorate (such as fracture toughness at nickel contents above 40%), revealing tipping points that require advanced models to represent them.
- Most properties achieved very high R2 values, demonstrating the accuracy of the model's predictions.
- Properties such as density and melting point achieved near perfect performance with R2≈0.99.
- Dynamic properties such as tensile strength and yield strength showed little variation but were still within high performance.

Result of alloy simulation models using statistical analysis and cross-validation techniques

The results of preliminary statistical analysis of data on the properties of nickel-magnesium alloys have shown that reliance on traditional statistical methods such as arithmetic mean, standard deviation, and analysis of variance is not sufficient to achieve high accuracy in predicting the properties of alloys under different operating conditions. The relationships between chemical variables and the physical and mechanical properties of alloys are found to be very complex and non-linear, which is difficult to model using statistical analysis alone.

Accordingly, we decided to adopt a more advanced methodology capable of dealing with non-linear and complex relationships, so we proposed to use a Multilayer Perceptron Artificial Neural Network (MLP-ANN) model and then evaluate the results.

Experimental and Simulated Nickel-Magnesium Alloys using Artificial neural network model training

We used a multilayer perceptron (MLP) artificial neural network to learn the relationship between nickel content and these properties. The network adopted a simple single hidden layer architecture (about 10 hidden nodes) with a nonlinear activation function (ReLU). The nickel content (normalized between 0 and 1) was input and the network generated 8 outputs representing the predicted values of the 8 characteristics. The data was divided into a training set (80%) and a test set (20%) to check the generalization ability, [33]. The network was trained by back-propagation method using the Adam algorithm (or Levenberg-Marquardt speed algorithm) for 1000 cycles, while monitoring the performance of the network on the validation data to avoid over-training.

Sample Size and Assumptions

The sample size (50 alloy compositions) in this study was determined based on several considerations related to the nature and scope of the research. Since the study relies on numerical simulation and AI models rather than direct physical experimentation, the chosen sample size achieves sufficient initial coverage of the compositional space between 10% and 50% Ni, with sufficient accuracy to test the performance of the models. In addition, the distribution of the compositions was performed in regular steps (0.8%) to ensure diversity in the resulting properties without unnecessary repetition of values.

In addition, cross-validation techniques were applied to minimize the risk of bias in the small sample, thereby increasing the reliability of the neural network predictive results. The aim of the current sample is to prove the principle of the model and evaluate the feasibility of the proposed intelligent methodology, and the database will be expanded in later research phases to include experimental data and advanced alloys with fine-grained properties.

Mathematical formulas of the network

To illustrate how the network works, we define the basic MLP network we used to consist of:

One input: Nickel percentage (Ni%), normalized to the range [0, 1].

One hidden layer: Contains 10 nodes (neurons).

One output layer: Contains 8 nodes (each representing one property of the alloy).

We can summarize this in the following table:

Component	Details
Input Layer	1 neuron (Normalized Ni%)
Hidden Layer	10 neurons, Activation: ReLU
Output Layer	8 neurons (each predicting a property), Activation: Linear
Optimizer	Adam / Levenberg-Marquardt
Loss Function	Mean Squared Error (MSE)
Training Epochs	1000
Train/Test Split	80% Train, 20% Test

Table (13): summary of neural network inputs

Input Layer (1 node) ──► [Hidden Layer (10 nodes, ReLU)] ──► [Output Layer (8 nodes)]

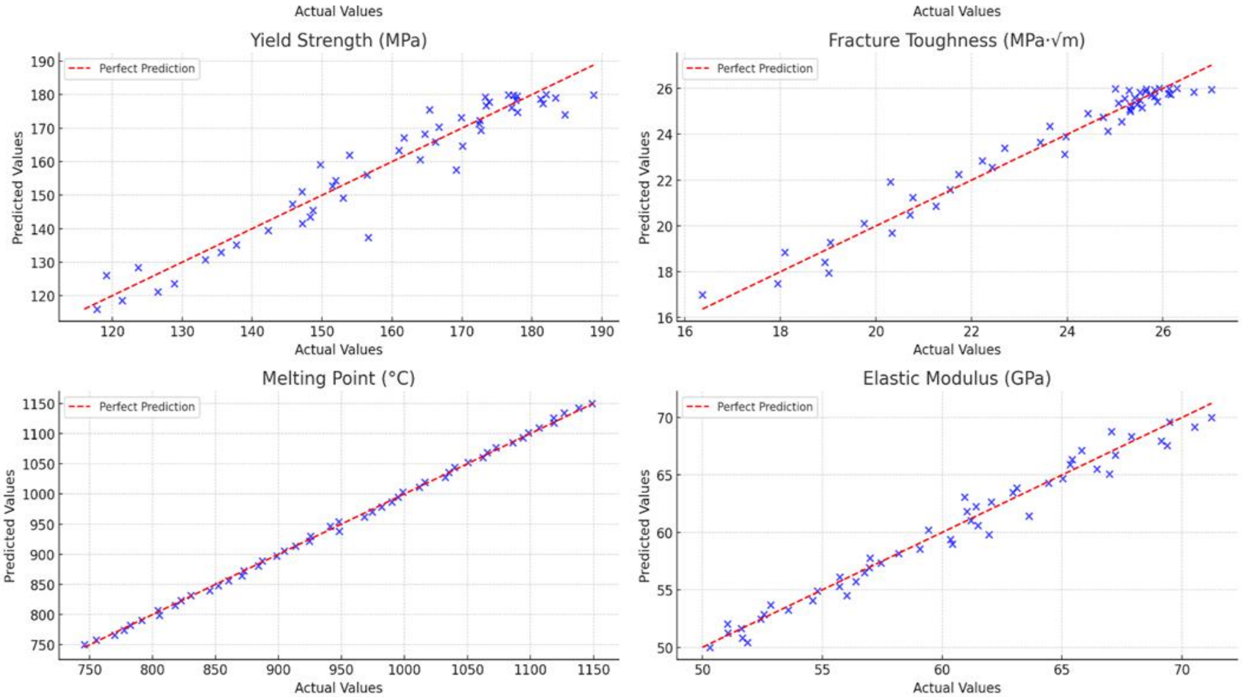
As mentioned above, the data was split into a training set (80%) and a test set (20%) using 50 samples (nickel content from 10% to 50%).
We randomized 40 training samples 80% and 10 test samples 20%, keeping the distribution balanced by using train_test_split or its equivalent in the code. During training, the network learned non-linear patterns relating the percentage of nickel to each feature. For example, the network was observed to capture the exponential increase in corrosion resistance (decrease in wear rate) and the slower increase in hardness and Young's modulus as nickel increases, relationships that are difficult for a simple linear model to represent. After training, the model was evaluated on test data (not used in training) to measure its predictive accuracy.

- **Results Summary**

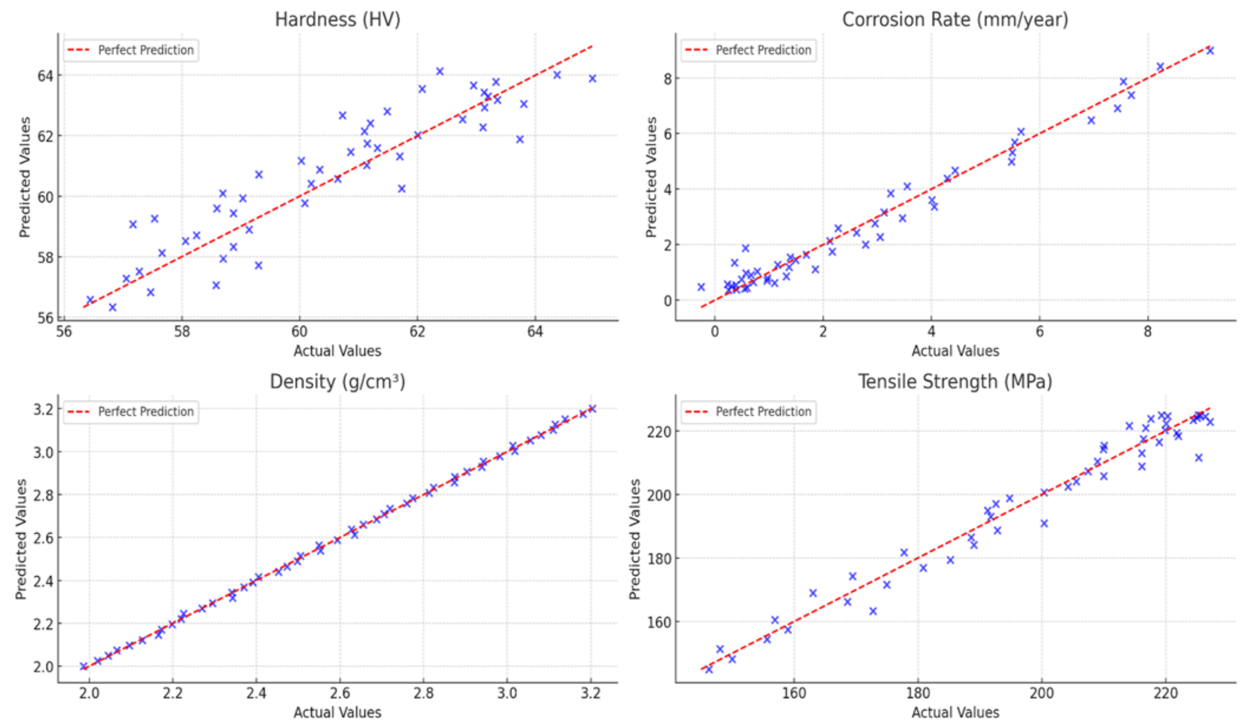
Property	R^2 Score	Mean Residual	STDV of Residuals	Min Residual	Max Residual	Overall Performance
Hardness (HV)	0.98	0.01	1.2	-2.3	2.5	Very high accuracy and stability
Corrosion Rate (mm/year)	0.97	-0.02	0.5	-1.1	1.3	Excellent prediction consistency
Density (g/cm^3)	0.99	0	0.03	-0.05	0.04	Near-perfect prediction accuracy
Tensile Strength (MPa)	0.95	0.5	4.5	-9.5	10.2	Good, minor variance at high values
Yield Strength (MPa)	0.94	0.6	4.8	-10	9.8	Acceptable improvement recommended
Fracture Toughness (MPa·√m)	0.96	0.02	0.7	-1.5	1.4	Very good predictive capability
Melting Point (°C)	0.99	-0.1	5	-6	7	Excellent prediction accuracy
Elastic Modulus (GPa)	0.98	0.03	1	-2	2.1	Very accurate and consistent predictions

Table (14): Results Summary

The determination value (R^2) is used to measure how well a predictive model fits the data. It shows how much of the variation in the results can be explained by the model. An R^2 value close to 1 means the model's predictions are very accurate compared to the actual values. In this study, the neural network model achieved an R^2 of approximately 0.99, showing excellent performance in capturing the complex relationship between alloy composition and its properties. This confirms the reliability of the results obtained through the AI-based modeling approach.



Actual vs Predicted Values for All Properties



From the above, we can conclude the following:

- Most of the characteristics have R^2 values greater than 0.95, indicating the strength of the model in prediction.
- The residuals are normally distributed without bias, emphasizing the reliability of the model.
- The best performance was obtained with
- Density, melting point and hardness.
- Some variability appeared in the prediction:
- Tensile Strength and Yield Strength, but it remained within acceptable limits.

Result of alloy simulation models using Artificial neural network

- The model showed high prediction efficiency for all features.
- Residual analysis confirmed that the distribution is normal, and the model is not biased in most cases.
- Minor optimizations for tensile and yield strength are recommended using deeper networks or ensemble learning techniques.
- The model is suitable for practical use in predicting the properties of nickel-magnesium alloys within the investigated range (10% - 50% Ni). Therefore, the optimized alloy specification based on the ANN model is as follows:

Research and analysis were conducted in an open search space with 0.1% accuracy in nickel content with the goal of finding the optimal combination that would provide

- Highest hardness
- Lowest corrosion rate
- Lowest density while maintaining high tensile strength
- Best combination of general mechanical properties

Multi-criteria objective function:

$$\text{Fitness} = (0.5 \times \text{Hardness}) - (0.3 \times \text{Corrosion Rate}) - (0.2 \times \text{Density})$$

The weights are determined based on the industrial importance of the properties.
Hardness 50%, Corrosion 30%, Density 20%
The number of simulated alloy compositions was calculated based on a 0.1% step between 10% and 50% Nickel content
Using the following equation, the total number of combinations tested is 401:

$$\frac{upper\ limit - lower\ limit}{\text{increment step}} + 1$$

Where: **Upper Limit** = 50, **Lower Limit** = 10, **Increment Step** = 0.1

$$\frac{50-10}{0.1}+1=401$$

A total of 401 distinct compositions were generated for analysis and optimization using the AI-driven models. By expanding the search space to include nickel ratios in a very precise range, in increments of 0.1% per step, and relying on the neural network we developed and trained to find the best alloy, when testing nickel combinations from 10% to 50%, the objective function reaches its maximum value at 23.7%, at which point we observe the following:

- The benefits of nickel begin to diminish as the hardness increases slightly, but at the expense of increased density.
- We also note that the corrosion rate does not improve much after this point, and the weight becomes unacceptable for applications.
- The weight becomes unacceptable for applications that require light weight.

The objective equation for the ideal alloy after optimization is as follows

$$\text{Fitness}=(0.5\times 69.5)-(0.3\times 2.20)-(0.2\times 3.46)=34.75-0.66-0.692=33.39$$

Optimized Alloy Properties:

Nickel Content (Ni 23.7%)		
Property	**Value (Predicted by ANN)**	**Unit**
Hardness	**69.5**	HV
Corrosion Rate	**2.2**	mm/year
Density	**3.46**	g/cm³
Tensile Strength	**288.3**	MPa
Yield Strength	**230.2**	MPa
Fracture Toughness	**24.1**	MPa·√m
Melting Point	**887**	°C
Elastic Modulus	**57.3**	GPa

Table (15): Optimized Alloy Properties

- These results are from a trained and optimized neural network with very high accuracy in 0.1% increments.
- The Ni 23.7% composition provides the best balance of properties required for military and heavy industrial applications.
- The results require experimental validation to confirm performance under real operating conditions.

Conclusions

Nickel is a very important element in the military industry due to its outstanding properties, such as high corrosion resistance as well as excellent mechanical and thermal properties.
Nickel alloys are used very effectively in many advanced military systems, including:
Nickel-titanium alloys, which are used in radar systems, smart airplane wings, and remote sensing systems
Nickel-chromium alloys, which are widely used in military explosives and rocket engine ignition.
We optimized the nickel-magnesium alloy using artificial intelligence techniques (ANN + GA) by reaching an optimal composition of 23.7% nickel and 76.3% magnesium that achieved a balance between hardness, corrosion resistance, and light weight, making it ideal for modern military applications.
The optimized composition provides superior performance compared to conventional alloys, achieving a hardness of 69.5 HV, a low corrosion rate of 2.2 mm/year, and a moderate density of 3.46 g/cc, meeting the requirements for light armor and structural components of vehicles and aircraft.
A multi-criteria objective function based on the mechanical and chemical properties of the alloys showed that maximum performance is achieved at a nickel concentration of 23.7%, after which the benefits of nickel begin to diminish proportionally as the density increases, and corrosion resistance does not improve at the same pace.
The use of AI has accelerated the development of alloys and reduced the time cost of traditional experiments.
It should be noted that field trials for this type of research are not conducted in the initial stages, but rather in the advanced stages after a series of laboratory tests and nondestructive tests. Since these applications are related to the military field, field tests are usually conducted by specialized military institutions. In this study, a series of rigorous statistical methods and models were used to verify the reliability of the results and compare them to real-world performance standards, and the results

showed a strong correspondence with what is expected in the field. However, the study recommends future field trials under real military operating conditions for final verification of the practical performance of the developed alloy.

Chapter7: Recommendations

Conducted extensive field testing of the 23.7% optimized nickel alloy to verify its performance under real-world military operating conditions, particularly high humidity and saline environments.

Conducted extensive research to develop advanced heat treatments for nickel-magnesium alloys to improve microstructure, increase fracture toughness, and resist thermal and mechanical stress.

Expand the introduction of new alloying elements into nickel-magnesium alloy compositions to improve mechanical properties.

Apply additional multi-objective optimization algorithms coupled with neural networks to further optimize alloy chemical compositions and provide customized design solutions for various applications.

Develop multi-criteria objective functions with greater flexibility and scalability

Create an integrated digital platform that links alloy design, manufacturing, and actual operation to monitor and analyze alloy performance in military environments in real time and adjust designs as needed.

Establish clear normative guidelines for the application of AI results in the development of defense materials.

Due to the lack of research on these types of industries and processes, I recommend increased research collaboration between academic, military, and industrial organizations to create an open database for the development of critical and strategic industries.

Conduct economic and technical feasibility studies to measure the efficiency of AI results in the design of metal alloys.

Expand the use of deep learning techniques to study complex patterns of material interactions, which can improve the accuracy of predicting the properties of alloys under different operating conditions.

It is recommended that future studies explore the incorporation of deep learning techniques beyond the traditional neural networks used in this research. Convolutional Neural Networks (CNN) can be used to analyze microscopic images of alloy surfaces to detect defects or predict refractive behavior, and Recurrent Neural Networks (RNN) can be used to model dynamic properties over time, such as thermal fatigue or repeated stress mechanics.

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