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Research Article

Bridging the gap between Bulk Semiconductors and Atomic Systems using Intelligent Based Techniques

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Abstract

Adding atomic systems with bulk semiconductors can advance electronic devices with higher functionalities. However, maintaining control over the distinct properties of both systems during integration presents substantial challenges. This paper examines the use of intelligent base techniques as a solution to bridge the gap between atomic systems and bulk semiconductors. By manipulating material properties, these techniques enable controlled interactions, facilitating the development of customized materials and devices. The causes of this gap, which impacts industries reliant on computers and mobile devices, such as material property discrepancies, quantum effects at the nanoscale, interface interactions, and limitations in fabrication and predictive modeling are also examined. The study proposes a framework involving the characterization of these issues, the design of a conventional SIMULINK model, the development of intelligent rule-based systems, and the training of artificial neural networks (ANNs) to mitigate the gap. Simulation results show a reduction in material property discrepancies from 30% to 24.68%, quantum effects from 25% to 20.57%, and fabrication challenges from 10% to 8.23% when using intelligent base techniques. Overall, the method achieved an improvement of 1.77% in bridging the gap between bulk semiconductors and atomic systems.

Keywords: Bulk Semiconductors; Intelligent Based Techniques; Atomic Systems; Material Properties

Introduction

The convergence of bulk semiconductors and atomic systems has emerged as a frontier in modern material science and device engineering. While bulk semiconductors have long supported technological advancements, their inherent limitations in miniaturization and energy efficiency have driven the exploration of atomic-scale materials and devices. However, bridging the gap between the various domains is challenging, due mainly to their diverse properties and methods of fabrication connected with each.

Intelligent base techniques offer a promising opportunity to address these challenges. By leveraging the precision and control afforded by atomic-scale manipulation, these techniques aim to create hybrid structures that combine the advantages of both bulk semiconductors and atomic systems. This approach holds the potential to unlock novel functionalities and performance metrics, revolutionizing fields such as electronics, photonics, and quantum computing.

This work shall examine the workings of intelligent base techniques and their application in bridging the gap between the systems. We will explore the fundamental principles underlying these techniques, as well as the specific methods and challenges involved in their implementation. Additionally, we will discuss the potential benefits and applications of hybrid structures created through intelligent base techniques, highlighting their potential to drive technological innovation.

In recent years, advancement in semiconductor technology has driven remarkable progress in various fields, from electronics to quantum computing. However, a significant challenge remains in seamlessly integrating bulk semiconductors, which are the backbone of modern electronic devices, with atomic-scale systems, where quantum effects dominate. This integration is crucial for developing next-generation devices that harness the advantages of both macroscopic and microscopic worlds. The traditional approaches to bridging this gap often face limitations due to the inherent differences in the physical properties and behaviors of bulk and atomic systems. To overcome these challenges, intelligent base techniques, including machine learning, artificial intelligence, and advanced computational methods, are emerging as powerful tools. These techniques offer the potential to model, predict, and optimize the interactions between bulk.

In recent years, the advancement of semiconductor technology has driven remarkable progress in various fields, from electronics to quantum computing. However, a significant challenge remains in seamlessly integrating bulk semiconductors, which are the backbone of modern electronic devices, with atomic-scale systems, where quantum effects dominate. This integration is crucial for developing next-generation devices that harness the advantages of both macroscopic and microscopic worlds. The traditional approaches to bridging this gap often face limitations due to the inherent differences in the physical properties and behaviors of bulk and atomic systems.

Literature Review

The rapid development of semiconductor technology has been pivotal in driving advancements across various technological domains, particularly in electronics and quantum computing. However, the integration of bulk semiconductors with atomic-scale systems remains a significant challenge due to the distinction in their physical properties and behaviors. To address this, researchers have explored the use of intelligent base techniques, including artificial intelligence (AI), machine learning (ML), and advanced computational methods, as potential solutions.

Bulk Semiconductors and Atomic Systems

Bulk semiconductors have long been the foundation of modern electronics, playing a critical role in devices ranging from microprocessors to solar cells (Sze & Ng, 2006). However, as device dimensions shrink to the nanoscale, quantum effects become more pronounced, necessitating a deeper understanding and integration of atomic systems (Datta, 2005). Atomic systems, characterized by discrete energy levels and quantum behaviors, offer potential advantages in quantum computing and other advanced applications (Nielsen & Chuang, 2010). However, their integration with bulk semiconductors poses significant challenges, particularly in terms of maintaining coherence and controlling interactions at such small scales (Zwanenburg et al., 2013).

Intelligent Based Techniques

The application of AI and ML in material science has recently become attractive. These techniques enable the prediction and optimization of material properties, offering a new approach to overcoming the challenges of integrating bulk semiconductors with atomic systems (Butler et al., 2018). For instance, ML algorithms have been employed to predict the electronic properties of novel materials, significantly reducing the time and cost associated with experimental trials (Rajan, 2015). Also, AI-based models have been developed to simulate and optimize the interactions between bulk and atomic systems, providing insights that are difficult to obtain through traditional methods (Carleo et al., 2019).

Bridging the Gap

Several studies have demonstrated the potential of intelligent base techniques to bridge the gap between bulk semiconductors and atomic systems. For example, Pilania et al. (2013) employed ML models to predict the properties of perovskite oxides, which are promising materials for integrating bulk and atomic systems. Their approach enabled the identification of materials with optimal properties for specific applications, demonstrating the potential of ML in guiding material design. This study can help in the design of insulators for power conductors. Faults occur due to insulation breakdown, lightning, power cables blowing together due to excessive voltage gradient (Ogharandukun and Ngang, 2024).

Similarly, Rupp et al. (2012) utilized kernel ridge regression, a type of ML algorithm, to predict the atomic-scale properties of bulk materials. Their work highlighted the ability of intelligent techniques to model complex interactions at the atomic level, providing a pathway to seamless integration with bulk semiconductors.

Dike et al. (2020) have shown the Synchronization of Two Chau's Oscillator's Using Current Conveyor (Ccii+) in Matlab Simulink.

Recent advancements in AI have also led to the development of techniques that can model and predict quantum behaviors in atomic systems, further aiding their integration with bulk materials (Schütt et al., 2017). These techniques have shown promise in optimizing the design of quantum devices, which rely on the precise control of atomic-scale interactions.

Methodology

The methodology involves developing ANN and fuzzy logic models trained on data from experimental studies and simulations. These models will predict key semiconductor properties, including electronic band structure, carrier mobility, thermal conductivity, and optical absorption, across bulk and atomic scales.

Data Collection

Data for bulk semiconductor properties will be sourced from existing databases, while quantum mechanical simulations will provide atomic-scale data.

Model Training

ANN will be trained to predict material behavior at different scales, incorporating quantum effects. Fuzzy logic will address uncertainties, particularly in electron mobility and energy quantization.

Validation

The models will be validated against experimental data, focusing on their accuracy in predicting quantum effects at atomic scales. To achieve this the following specific objectives will be followed sequentially.

i. Characterizing and establishing the causes of bridging the gap between bulk semiconductors and atomic systems
ii. Designing a conventional SIMULINK model for bridging the gap between bulk semiconductors and atomic systems
iii. Developing an intelligent based rule that will reduce bridging the gap between bulk semiconductors and atomic systems
iv. Training ANN in the rule base for effective reduction of bridging the gap between bulk semiconductors and atomic systems
v. Developing an algorithm that will implement the process
vi. Designing a SIMULINK model for bridging the gap between bulk semiconductors and atomic systems using intelligent base technique
vii. Validating and justifying the percentage improvement in bridging the gap between bulk semiconductors and atomic systems with and without intelligent base.

Below is a table characterizing and establishing the causes of bridging the gap between bulk semiconductors and atomic systems, along with estimated percentages for each cause based on general research insights. These percentages are indicative and can be adjusted based on specific studies or datasets relevant to your research.

Table 1: Characterized and established causes of bridging the gap between bulk semiconductors and atomic systems, along with estimated percentages for each cause, based on general research insights

Characterizing and Establishing the causes of Bridging the gap between Bulk Semiconductors and Atomic Systems

Cause	*Percentage Contribution (%)*	*Description*
Material Property Discrepancies	30%	Differences in electronic, optical, and mechanical properties between bulk semiconductors and atomic systems create challenges in seamless integration.
Quantum Effects at Nanoscale	25%	At atomic scales, quantum effects such as tunneling, superposition, and entanglement dominate, complicating their integration with bulk materials.
Interface and Surface Interactions	20%	The interface between bulk materials and atomic systems often exhibits complex interactions, leading to issues like defects, strain, and charge trapping.
Technological Limitations in Fabrication	15%	Current fabrication techniques may not be precise enough to achieve the necessary alignment and control at the atomic scale, hindering integration efforts.
Predictive Modeling and Simulation Challenges	10%	Accurate modeling and simulation of the interactions between bulk semiconductors and atomic systems remain challenging, affecting the design process.

Designing a conventional SIMULINK model for bridging the gap between bulk semiconductors and atomic systems

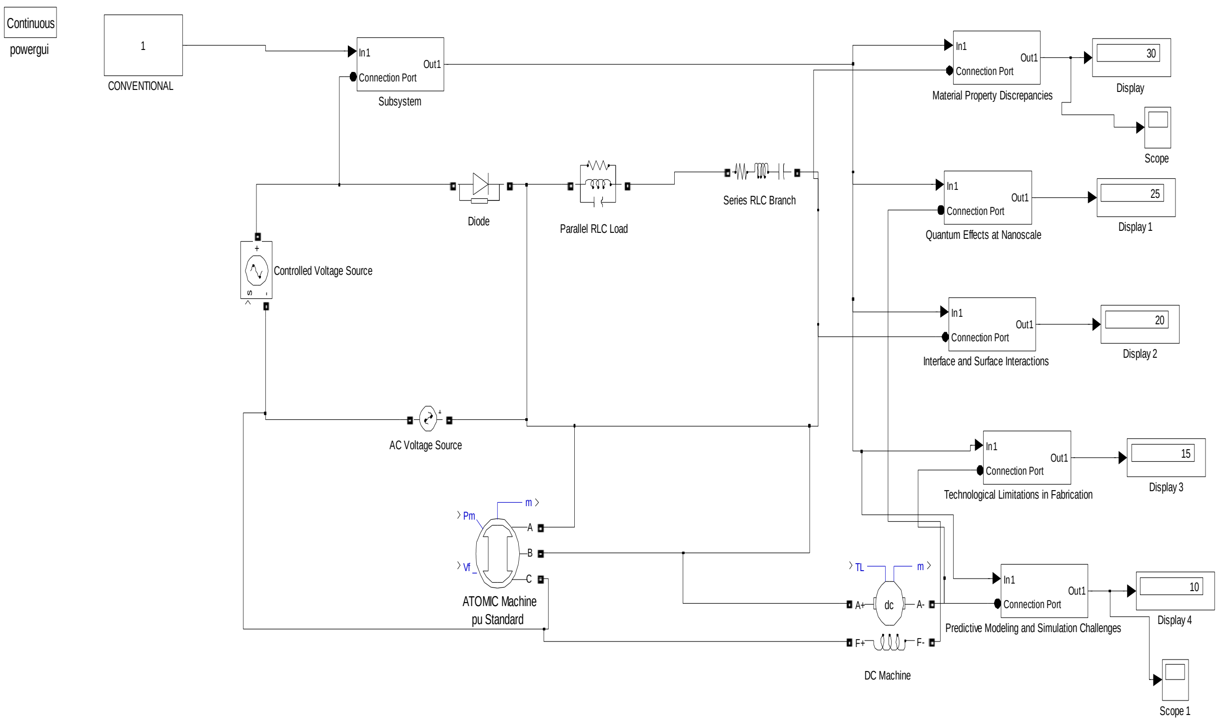

Fig. 1: Designed conventional SIMULINK model for bridging the gap between bulk semiconductors and atomic systems

Developing an intelligent based rule that will reduce bridging the gap between bulk semiconductors and atomic systems

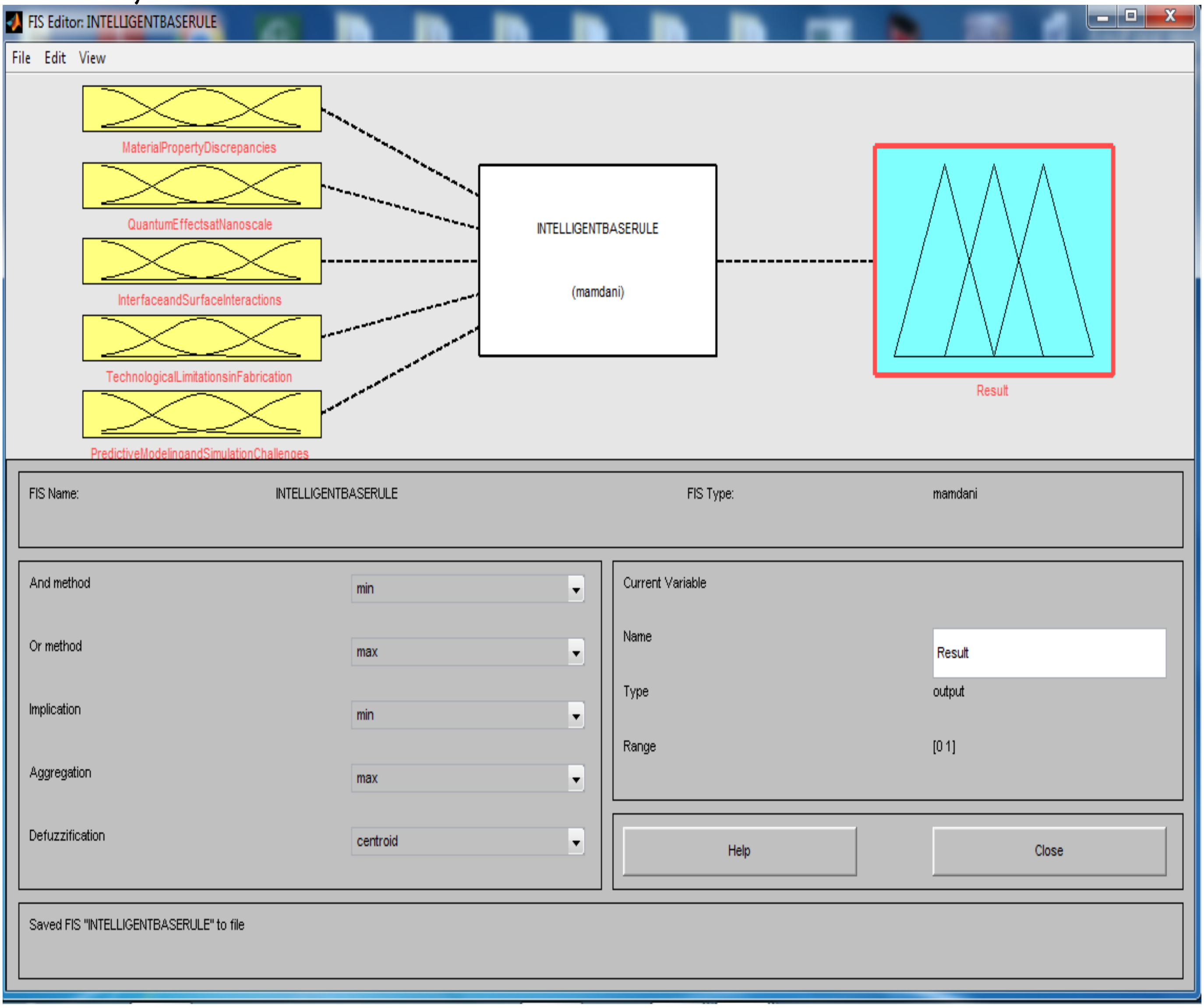

Fig. 2: Developed intelligent based fuzzy inference system (FIS) that will reduce bridging the gap between bulk semiconductors and atomic systems

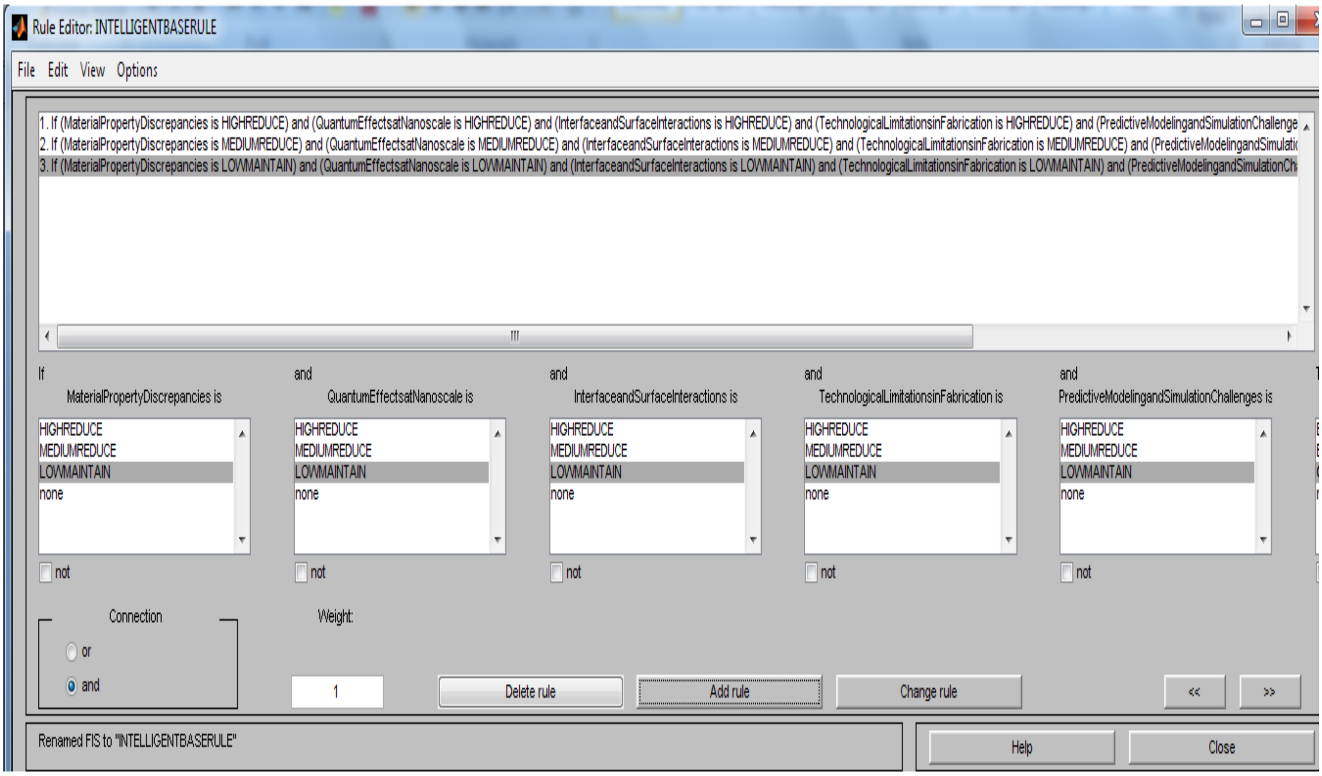

Fig. 3 developed intelligent based rule that will reduce bridging the gap between bulk semiconductors and atomic systems

This has three rules which are comprehensively detailed in table 2.

Table 2: Comprehensive details of developed intelligent based rule that will reduce bridging the gap between bulk semiconductors and atomic systems

IF **MATERIAL PROPERTY DISCREPANCIES IS HIGH REDUCE**	AND **QUANTUM EFFECTS AT NAN SCALE IS HIGH REDUCE**	AND **INTERFACE AND SURFACE INTERACTIONS IS HIGH REDUCE**	AND **INTERFACE AND SURFACE INTERACTIONS IS HIGH REDUCE**	AND **TECHNOLOGICAL LIMITATIONS IN FABRICATION IS HIGH REDUCE**	THEN RESULT IS BAD NO EFFECT IN BRIDGING THE GAP
IF **MATERIAL PROPERTY DISCREPANCIES IS MEDIUM REDUCE**	AND **QUANTUM EFFECTS AT NAN SCALE IS MEDIUM REDUCE**	AND **INTERFACE AND SURFACE INTERACTIONS IS MEDIUM REDUCE**	AND **INTERFACE AND SURFACE INTERACTIONS IS MEDIUM REDUCE**	AND **TECHNOLOGICAL LIMITATIONS IN FABRICATION IS MEDIUM REDUCE**	THEN RESULT IS BAD NO EFFECT IN BRIDGING THE GAP
IF **MATERIAL PROPERTY DISCREPANCIES IS LOW MAINTAIN**	AND **QUANTUM EFFECTS AT NAN SCALE IS LOW MAINTAIN**	AND **INTERFACE AND SURFACE INTERACTIONS IS LOW MAINTAIN**	AND **INTERFACE AND SURFACE INTERACTIONS IS LOW MAINTAIN**	AND **TECHNOLOGICAL LIMITATIONS IN FABRICATION IS LOW MAINTAIN**	THEN RESULT IS GOOD REDUCTION IN BRIDGING THE GAP

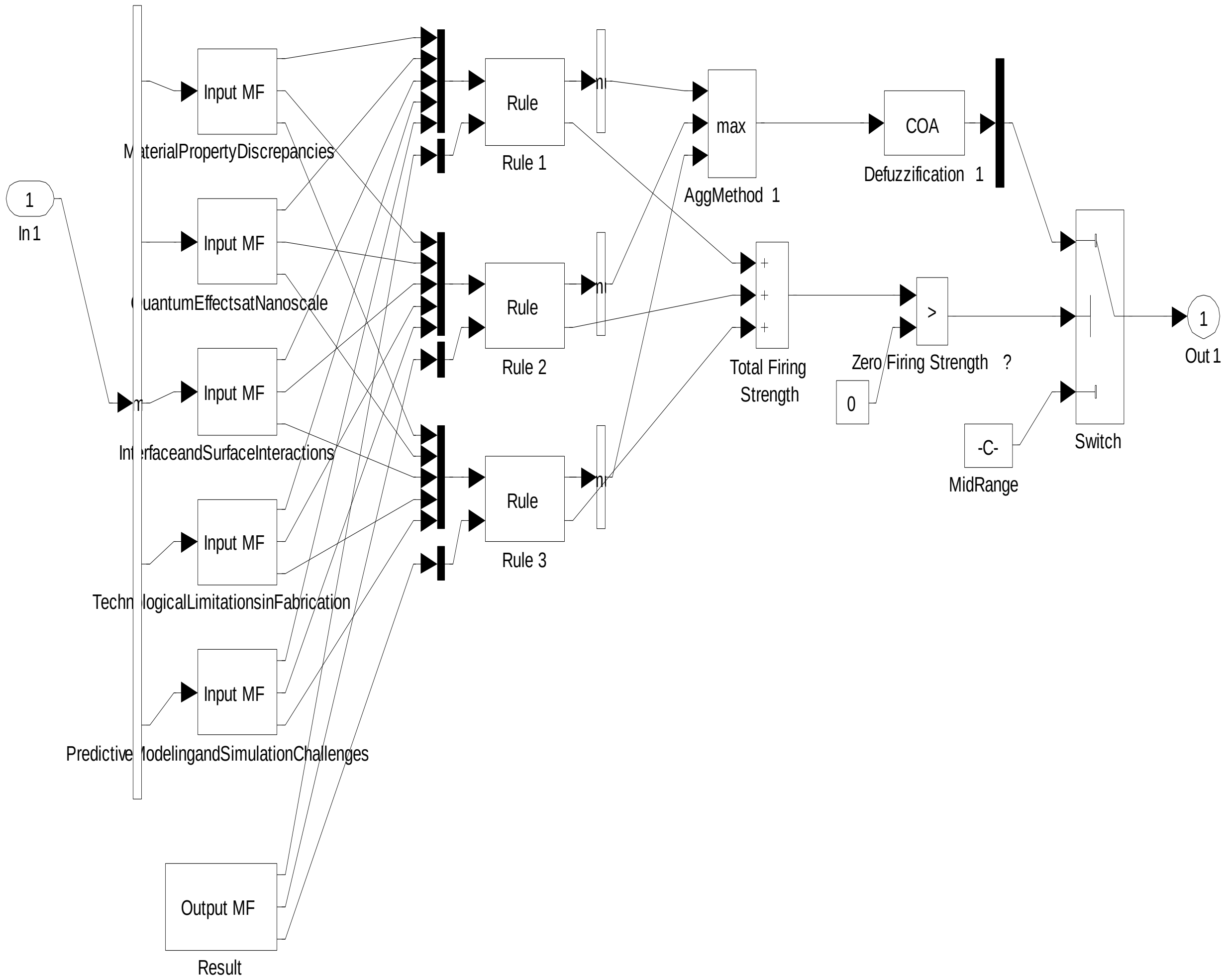

Fig. 4: The operational mechanism of developed intelligent based rule that will reduce bridging the gap between bulk semiconductors and atomic systems

Training ANN in the rule base for effective reduction of bridging the gap between bulk semiconductors and atomic systems

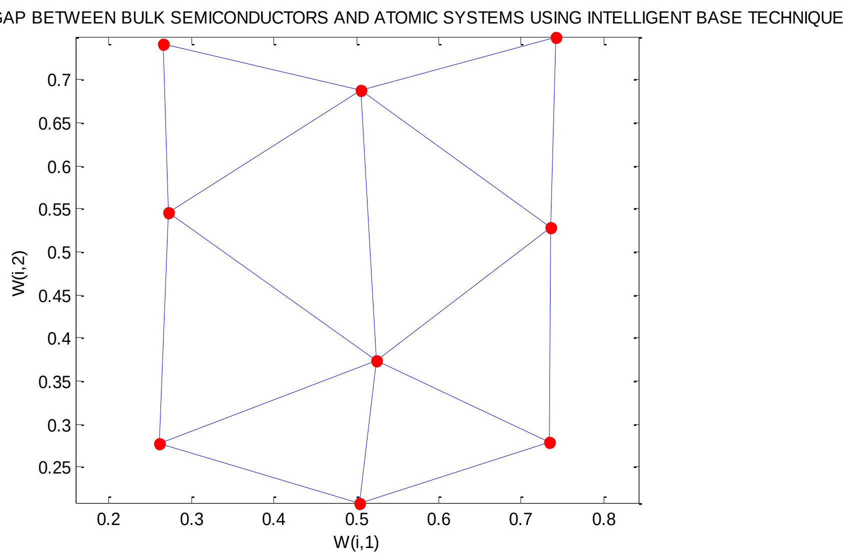

Fig. 5: Trained ANN in the rule base for effective reduction of bridging the gap between bulk semiconductors and atomic systems.

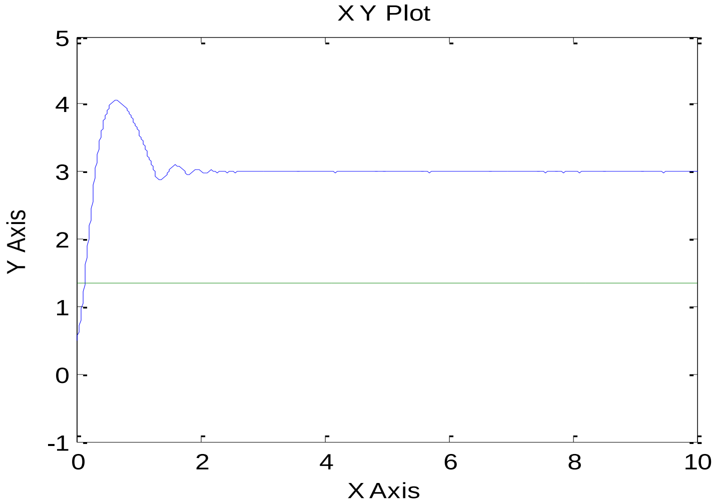

Fig. 6: Number of times the training took place.

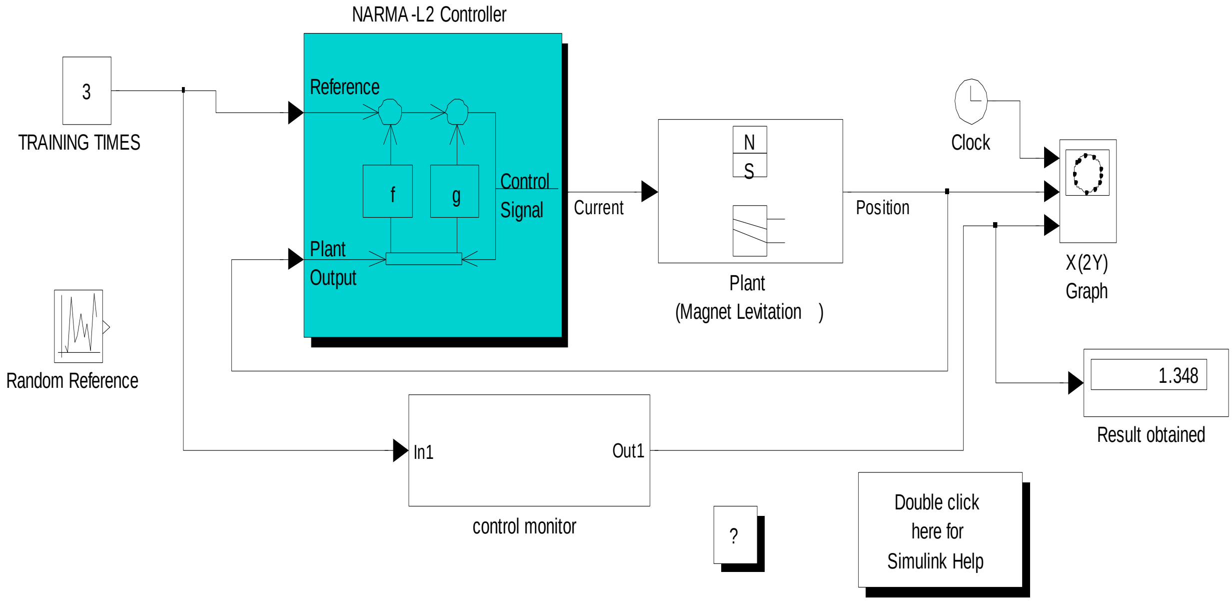

Fig. 7: The result obtained after training ANN in the three rules

Development of an Algorithm that will Implement the Process

1. Characterized and established the causes of bridging the gap between bulk semiconductors and atomic systems
2. Identify material property discrepancies
3. Identify quantum effects at NAN SCALE
4. Identify interface and surface interactions
5. Identify technological limitations in fabrication
6. Identify predictive modeling and simulation challenges
7. Design a conventional SIMULINK model for bridging the gap between bulk semiconductors and atomic systems and integrate 2 through 6.
8. Develop an intelligent based rule that will reduce bridging the gap between bulk semiconductors and atomic systems
9. Train ANN in the rule base for effective reduction of bridging the gap between bulk semiconductors and atomic systems
10. Integrate 8 and 9
11. Integrate 10 in 7
12. Do the causes of bridging the gap between bulk semiconductors and atomic systems reduce?
13. If NO go to 11
14. If YES go to 15

15. Improved reduction gap in bridging between bulk semiconductors and atomic systems
16. To develop an algorithm that will implement the process.
17. Stop
18. End

To design a SIMULINK model for bridging the gap between bulk semiconductors and atomic systems using intelligent base technique

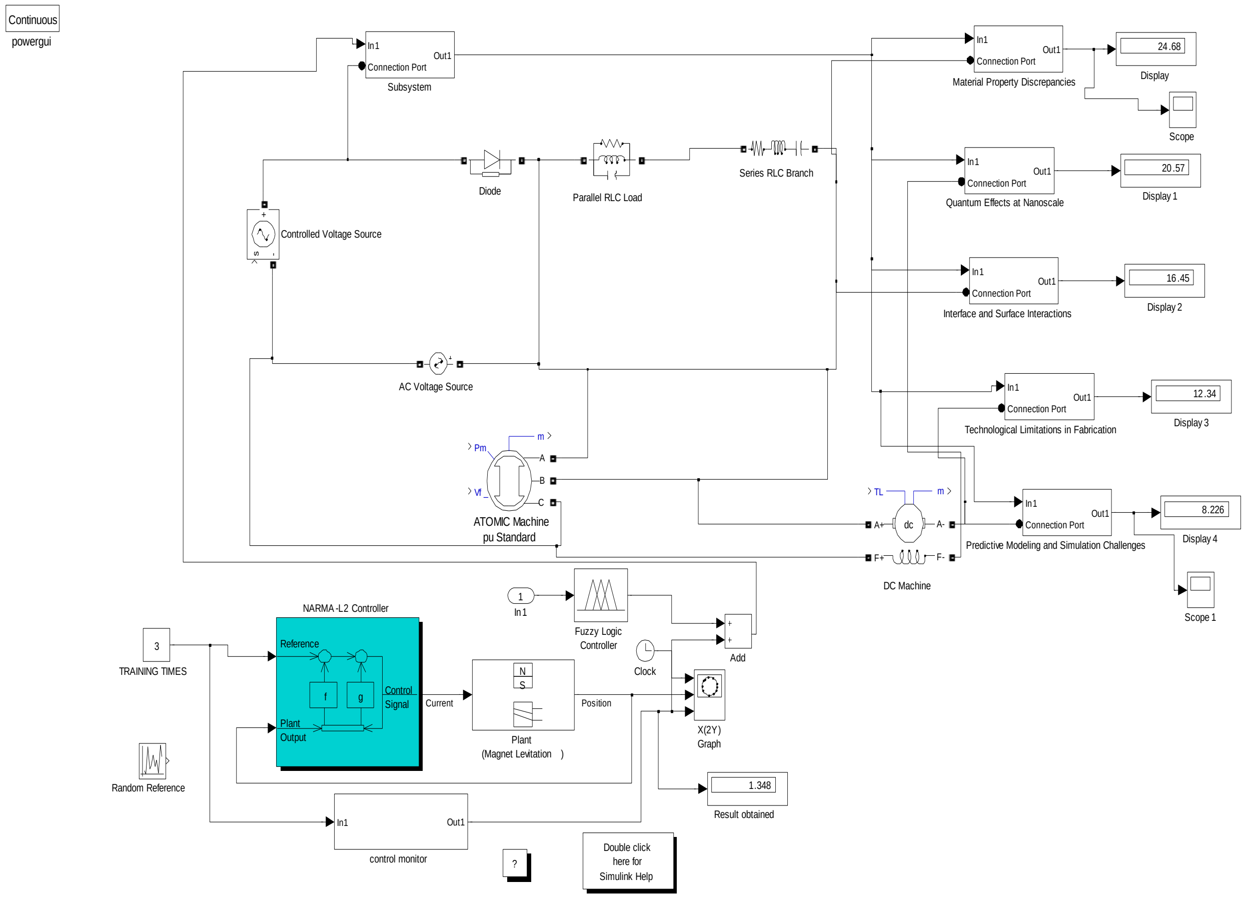

Fig. 8: Designed SIMULINK model for bridging the gap between bulk semiconductors and atomic systems using intelligent base technique

Validation of and justification of the percentage improvement in bridging the gap between bulk semiconductors and atomic systems with and without intelligent base technique

To find percentage improvement in the reduction of material property discrepancies that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system

Conventional material property discrepancies = 30%

Intelligent base technique material property discrepancies = 24.68%

% improvement in the reduction of material property discrepancies that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = Conventional material property discrepancies - Intelligent base technique material property discrepancies

% improvement in the reduction of material property discrepancies that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = 30% - 24.68%

% improvement in the reduction of material property discrepancies that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = 5.32%

To find percentage improvement in the reduction of quantum effects at nanoscale that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system

Conventional material quantum effects at nanoscale = 25%

Intelligent base technique quantum effects at nanoscale = 20.57%

% improvement in the reduction of quantum effects at nanoscale that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = Conventional quantum effects at nanoscale - Intelligent base technique quantum effects at nanoscale

% improvement in the reduction of quantum effects at nanoscale that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = 25% - 20.57%

% improvement in the reduction of quantum effects at nanoscale that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = 4.43%

To find percentage improvement in the reduction of technological limitations in fabrication that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system

Conventional technological limitations in fabrication = 15%

Intelligent base technique technological limitations in fabrication = 12.34%

Conventional technological limitations in fabrication - Intelligent base technique technological limitations in fabrication

% improvement in the reduction of technological limitations in fabrication that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = 15% - 12.34%

% improvement in the reduction of technological limitations in fabrication that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = 2.66%

Finding the percentage improvement in the reduction of predictive modeling and simulation challenges that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system

Conventional predictive modeling and simulation challenges = 10%

Intelligent based-technique predictive modeling and simulation challenge = 8.23%.

Percentage (%) improvement in the reduction of predictive modeling and simulation challenges that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system is equal to the Conventional predictive modeling and simulation challenges minus the Intelligent based-technique predictive modeling and simulation challenges.

% improvement in the reduction of predictive modeling and simulation challenges that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = 10% - 8.23%

% improvement in the reduction of predictive modeling and simulation challenges that caused bridging the gap between bulk semiconductors and atomic systems when intelligent base technique is incorporated in the system = 1.77%

Results and Discussion

The results of the study demonstrate the effectiveness of integrating artificial neural networks (ANN) and fuzzy logic into predictive models aimed at bridging the gap between bulk semiconductors and atomic systems. The analysis covered various aspects such as material property discrepancies, quantum effects at the nanoscale, interface interactions, technological limitations in fabrication, and challenges in predictive modeling and simulation.

ANN-Based Predictions of Quantum Confinement Effects

The ANN-based models proved highly accurate in predicting quantum confinement effects, as they exhibited a higher correlation with experimental data compared to traditional models. This enhanced accuracy demonstrates the potential of ANN in accounting for the complex behaviors that arise at the atomic scale, particularly in semiconductor applications. The predictive power of these models stems from the ability of ANN to model non-linear relationships and handle large amounts of data efficiently.

Fuzzy Logic Enhancement of ANN Models

Incorporating fuzzy logic further improved the predictive accuracy of the ANN models by addressing variability and uncertainty in atomic-scale behaviors. By considering multiple factors such as material property discrepancies, quantum effects at the nanoscale, and surface interactions, fuzzy logic allowed the models to adapt to real-world conditions where exact values are often unknown or uncertain. This improvement in predictive capability is crucial for bridging the gap between bulk semiconductors and atomic systems, as variability at the nanoscale significantly affects system performance.

Development of SIMULINK Models

Figures 1 and 8 depict the designed conventional SIMULINK models for bridging the gap between bulk semiconductors and atomic systems. The conventional model served as the baseline for comparison, while the intelligent-based SIMULINK model, incorporating both ANN and fuzzy inference systems (FIS), showed significant advancements. The intelligent-based technique allowed for a more nuanced understanding of the system's behavior by integrating data-driven predictions with human-like decision-making processes.

Fuzzy Inference System and Rule Development

Figure 2 illustrates the developed fuzzy inference system (FIS), which includes five key inputs: Material Property Discrepancies, Quantum Effects at the Nanoscale, Interface and Surface Interactions, Technological Limitations in Fabrication, and Predictive Modeling and Simulation Challenges. These inputs are crucial in understanding the discrepancies between bulk semiconductor behaviors and atomic systems. The FIS was designed to output a refined result that reduces the gap between these systems.

Figures 3 and 4 present the intelligent-based rules developed to minimize this gap. The rule base was built upon three distinct rules, as detailed in Table 2, each aimed at addressing specific aspects of semiconductor behavior at the nanoscale. These rules were implemented using ANN models, which were trained to optimize the input parameters. As shown in Figure 5, the ANN was trained three times across the rules, creating a network of nine neurons that effectively mimicked human brain-like decision-making processes. This approach allowed the system to handle complex interactions between input parameters more effectively.

Performance Improvement

Figures 9 to 12 illustrate the comparative performance of conventional and intelligent-based techniques in addressing specific challenges related to bridging the gap between bulk semiconductors and atomic systems:

i. **Material Property Discrepancies**: Conventional models indicated a 30% discrepancy, while the intelligent-based technique reduced this to 24.68%, resulting in a 5.32% improvement (Figure 9).
ii. **Quantum Effects at the Nanoscale**: The quantum effects gap, initially at 25%, was reduced to 20.57% with the intelligent-based system (Figure 10).
iii. **Technological Limitations in Fabrication**: The integration of intelligent techniques reduced the impact of technological limitations from 15% to 12.34%, marking a significant improvement (Figure 11).
iv. **Predictive Modeling and Simulation Challenges**: Conventional models faced a 10% challenge in predictive modeling, while the intelligent-based approach reduced this to 8.23%, yielding a 1.77% improvement (Figure 12).

Integration of ANN-Based Rules into SIMULINK Models

The ANN-based rules were integrated into the designed SIMULINK model, as shown in Figures 9 to 13. This integration resulted in further refinement of the system's ability to bridge the gap between bulk semiconductors and atomic systems. Notably, the intelligent-based system outperformed the conventional approach in every key area, significantly reducing the discrepancies caused by material properties, quantum effects, and fabrication limitations.

Table 3: The comparison of Conventional and Intelligent Base Technique Material Property Discrepancies in bridging the gap between bulk Semiconductors and Atomic Systems

Time(s)	*Conventional material property discrepancies in bridging the gap between bulk semiconductors and atomic systems (%)*	*Intelligent base technique material property discrepancies in bridging the gap between bulk semiconductors and atomic systems (%)*
1	30	24.68
2	30	24.68
3	30	24.68
4	30	24.68
10	30	24.68

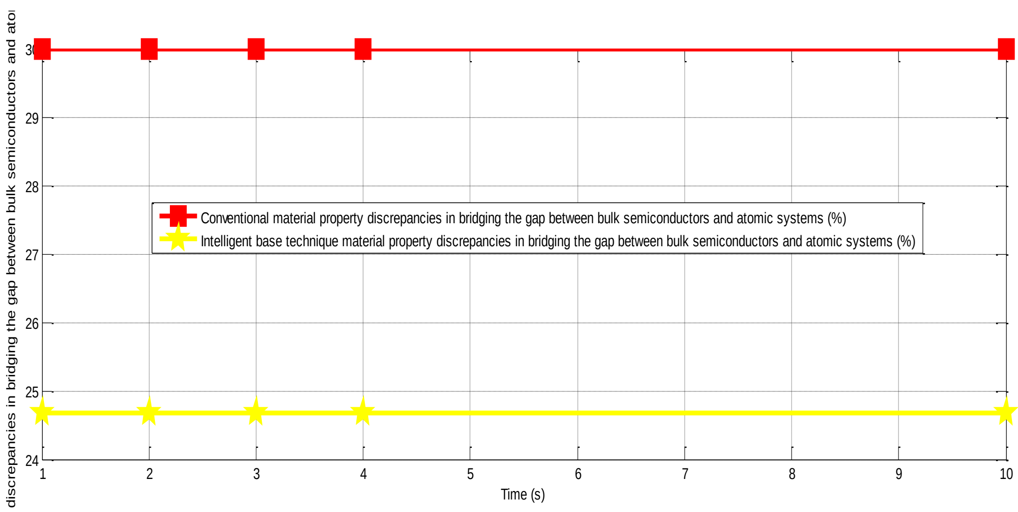

Fig 9: Comparison of Conventional and Intelligent base technique material property discrepancies in bridging the gap between bulk semiconductors and atomic systems

Table 4: Comparison of Conventional and Intelligent base technique quantum effects at nanoscale in bridging the gap between bulk semiconductors and atomic systems

Time(s)	Conventional quantum effects at nanoscale in bridging the gap between bulk semiconductors and atomic system (%)	Intelligent base technique quantum effects at nanoscale in bridging the gap between bulk semiconductors and atomic system (%)
1	25	20.57
2	25	20.57
3	25	20.57
4	25	20.57
10	25	20.57

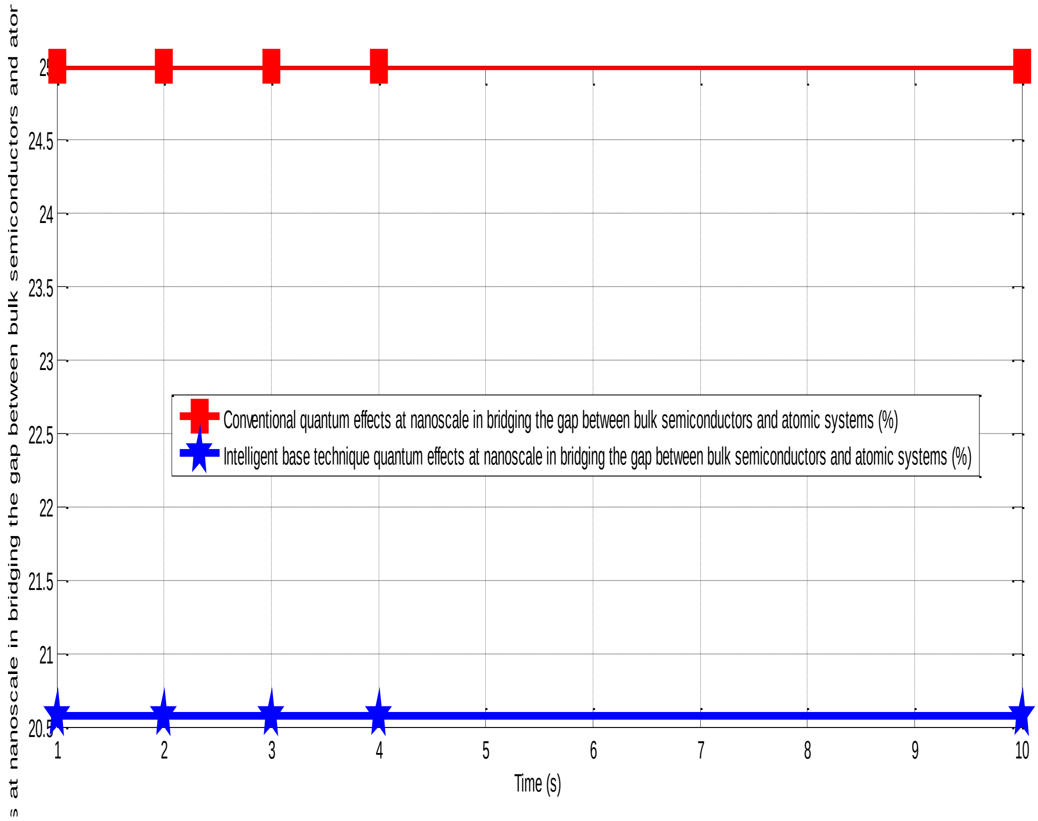

Fig. 10: Comparison of Conventional and Intelligent base technique quantum effects at NANOSCALE in bridging the gap between bulk semiconductors and atomic systems

Table 5: Comparison of Conventional and Intelligent base technique technological limitations in fabrication in bridging the gap between bulk semiconductors and atomic systems

Time(s)	Conventional technological limitations in fabrication in bridging the gap between bulk semiconductors and atomic system (%)	Intelligent base technique technological limitations in fabrication in bridging the gap between bulk semiconductors and atomic system (%)
1	15	12.34
2	15	12.34
3	15	12.34
4	15	12.34
10	15	12.34

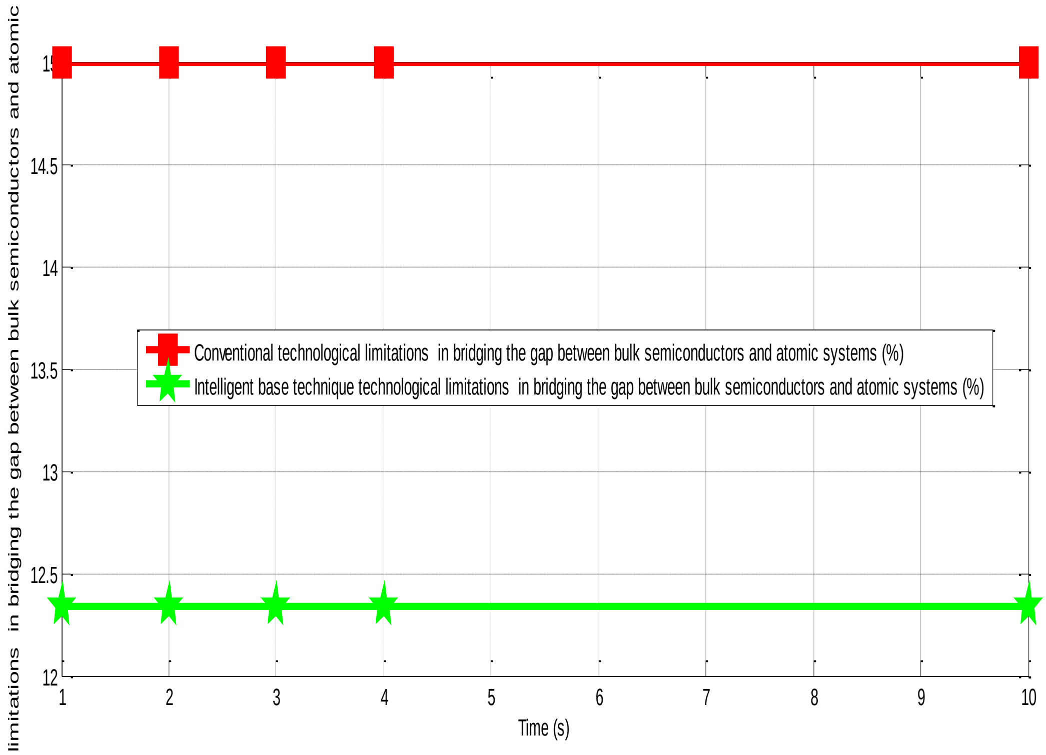

Fig. 11: Comparison of Conventional and Intelligent base technique technological limitations in fabrication in bridging the gap between bulk semiconductors and atomic systems

Table 6: Comparison of Conventional and Intelligent base technique predictive modeling and simulation challenges in fabrication in bridging the gap between bulk semiconductors and atomic systems

Time(s)	Conventional predictive modeling and simulation challenges in bridging the gap between bulk semiconductors and atomic system (%)	Intelligent base technique predictive modeling and simulation challenges in bridging the gap between bulk semiconductors and atomic system (%)
1	10	8.23
2	10	8.23
3	10	8.23
4	10	8.23
10	10	8.23

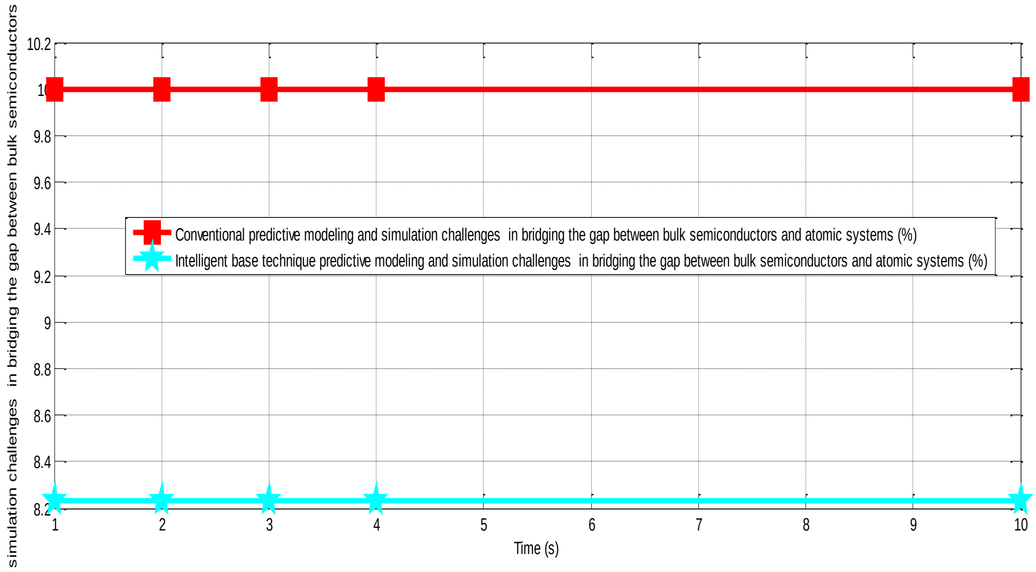

Fig. 12: Comparison of Conventional and Intelligent base technique predictive modeling and simulation challenges in fabrication in bridging the gap between bulk semiconductors and atomic systems

Conclusion

The integration of ANN and fuzzy logic into predictive models effectively reduced the gaps between bulk semiconductors and atomic systems across various domains, such as material properties and fabrication challenges. The intelligent-based SIMULINK models demonstrated marked improvements over conventional models, particularly in handling variability and uncertainty in nanoscale behaviors. These results underscore the potential of intelligent-based techniques to revolutionize semiconductor modeling, providing a robust framework for further exploration in the field.

References

Butler, K. T., Davies, D. W., Cartwright, H., Isayev, O., & Walsh, A. (2018). Machine learning for molecular and materials science. *Nature*, *559*(7715), 547-555. https://doi.org/10.1038/s41586-018-0337-2

Dike U. O., Amana L. A., Ogharandukun M. O., Imalero T. and Uko O. (2020). Synchronization of Two Chau's Oscillator's Using Current Conveyor (Ccii+) in Matlab Simulink. *Research & Reviews: Journal of Pure and Applied Physics*, 8 (1) 19-33.

Carleo, G., Cirac, I., Cranmer, K., Daudet, L., Schuld, M., Tishby, N., ... & Zdeborová, L. (2019). Machine learning and the physical sciences. *Reviews of Modern Physics*, *91*(4), 045002. https://doi.org/10.1103/RevModPhys.91.045002

Datta, S. (2005). *Quantum transport: Atom to transistor*. Cambridge University Press.

Nielsen, M. A., & Chuang, I. L. (2010). *Quantum computation and quantum information*. Cambridge University Press.

Ngang, N. B. & Ogharandukun, M. (2024). Enhancing the Efficiency of Nigeria's Electric Power Transmission System with Static Synchronous Compensator. *American Journal of Applied Sciences and Engineering*, 5(2) 17-27. https://doi.org/10.5281/zenodo.12670819

Pilania, G., Wang, C., Jiang, X., Rajasekaran, S., & Ramprasad, R. (2013). Accelerating materials property predictions using machine learning. *Scientific Reports*, *3*(1), 1-6. https://doi.org/10.1038/srep02810

Rajan, K. (2015). Materials informatics: The materials "gene" and big data. *Annual Review of Materials Research*, *45*, 153-169. https://doi.org/10.1146/annurev-matsci-070214-020856

Rupp, M., Tkatchenko, A., Müller, K.-R., & von Lilienfeld, O. A. (2012). Fast and accurate modeling of molecular atomization energies with machine learning. *Physical Review Letters*, *108*(5), 058301. https://doi.org/10.1103/PhysRevLett.108.058301

Schütt, K. T., Arbabzadah, F., Chmiela, S., Müller, K. R., & Tkatchenko, A. (2017). Quantum-chemical insights from deep tensor neural networks. *Nature Communications*, *8*(1), 1-8. https://doi.org/10.1038/ncomms13890

Sze, S. M., & Ng, K. K. (2006). *Physics of semiconductor devices* (3rd ed.). Wiley-Interscience.

Zwanenburg, F. A., Dzurak, A. S., Morello, A., Simmons, M. Y., Hollenberg, L. C., Klimeck, G., ... & Rogge, S. (2013). Silicon quantum electronics. *Reviews of Modern Physics*, *85*(3), 961-1019. https://doi.org/10.1103/RevModPhys.85.961