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Transfer Learning-driven Comparative Analysis of GA, PSO, and NSGA-II Over FIS for Enhanced Energy Efficiency in Assisted Living Settings

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Abstract: This research explores the integration of transfer learning within optimization algorithms Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II) over Fuzzy Systems (FIS) for enhancing energy efficiency in assisted living environments. We optimize FIS models by testing various transfer learning combinations: GA to PSO, GA to NSGA-II, PSO to NSGA-II, and GA to NGSA-II. Results show that PSO to NSGA-II delivers the best performance. GA to NSGA-II also showed notable improvement, benefiting from NSGA-II's efficient Pareto front exploration following GA's broad search capabilities. GA to PSO demonstrated slight improvement over GA alone, but PSO after GA performed worse due to premature convergence and reduced genetic diversity. In contrast, GA to NSGA-II retained better solution diversity, improving multi-objective optimization outcomes. These findings highlight the potential of transfer learning to enhance energy optimization in complex assisted living systems and provide deeper insights into its role in improving energy efficiency through strategic algorithmic pairing.

Keywords: Transfer learning fuzzy inference systems, Energy optimization, Genetic algorithms, PSO, Multi-objective optimization, Pareto front.

1. Introduction

The optimization of energy efficiency in assisted living environments is a critical area of research, as it can directly contribute to the sustainability, "green environment", and cost-effectiveness of these settings. To address this, advanced optimization techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Fuzzy Inference Systems (FIS) are being increasingly explored to improve energy usage while balancing comfort [1]. Despite improvements, there were limitations due to search space convergence and genetic diversity issues. Several studies have demonstrated the power of MOEAs (Multi-Objective Evolutionary Algorithms) in optimizing complex systems, such as building energy efficiency [2]. For example, SMOPSO/D (Simple Multi-Objective Particle Swarm Optimization with Decomposition), a multi-agent evolutionary algorithm, has been used to optimize energy-efficient building designs by balancing objectives such as energy use, cost, and comfort [3]. Enhanced algorithms like NSGA-II have also been integrated with multi-agent systems to improve solution diversity and convergence rates in building energy design optimization [4]. By underlying multi-agent strategies, these algorithms can dynamically adjust to changing environmental and user conditions, making them ideal for assisted living environments where comfort and energy efficiency are often at odds. Transfer learning, which highlights past knowledge to accelerate learning in new tasks, has shown promise in improving the efficiency of evolutionary algorithms. In dynamic multi-objective optimization problems (DMOPs), reusing past experiences can enhance both robustness and performance of algorithms like NSGA-II, MOPSO (Multi-Objective PSO), and RM-MEDA (Regularity Model-Based Multi-Objective Estimation of Distribution Algorithm) [5]. For instance, PSO-based controllers have outperformed traditional methods in load frequency control by improving system performance and reducing convergence time [6]. Hybrid approaches have also demonstrated improved optimization performance. For example, the IHOGCP algorithm, which combines GA and PSO, has been used to optimize task offloading in the Internet of Reconfigurable Things (IoRT), enhancing transmission rates and reducing energy consumption under deadlines [7]. Such hybrid models have the potential to improve FIS based energy prediction in assisted living environments by enabling real-time adaptive energy management. Multi-agent systems can dynamically respond to occupant behavior and environmental changes, making them suitable for complex systems like assisted living environments, [8]. Transfer learning has also been applied to dynamic community detection in complex networks, with algorithms like TMOGA (Transfer Learning-Based Multi-Objective Genetic Algorithm) outperforming traditional methods in terms of efficiency and convergence [9]. Despite its success in classification tasks, few approaches have targeted regression problems in fuzzy systems. Traditional fuzzy regression transfer learning often performs well only in constrained domains with limited target data, limiting its practical application [10]. A key challenge in fuzzy transfer learning is aligning data distributions between the source and target domains. Unlike conventional kernel-based nonlinear mappings, fuzzy-based approaches use transformations in the antecedent part of fuzzy rules, making the process more interpretable [11]. Another challenge in fuzzy transfer learning is how to effectively merge and use knowledge from multiple source domains [12]. At the best of our knowledge there are algorithms that explore two approaches for combining fuzzy rules from different domains in regression tasks: one for homogeneous domains and another for heterogeneous domains. In homogeneous cases, knowledge is integrated directly through fuzzy rules, while at heterogeneous cases, knowledge is merged in the form of both data and fuzzy rules. While this research focuses on dynamic FIS surface optimization, its insights are applicable to IoT systems in assisted living environments, where dynamic changes in occupant behavior and environmental conditions require adaptive energy management systems, as demonstrated in our previous work [1]. By incorporating transfer learning from GA (Genetic Algorithm) to PSO (Particle Swarm Optimization), GA to NSGA-II, and PSO to Non-dominated Sorting Genetic Algorithm II (NSGA-II), it is possible to harness previous optimization experiences to enhance the performance of FIS controllers, resulting in more efficient energy management. Reusing past optimization cycles allows the FIS-based models to adapt more effectively to changes in energy usage patterns and occupant behavior. This approach aims to provide improved long-term energy efficiency in assisted living environments, ensuring better comfort, lower costs, and more sustainable operation.

Applying transfer learning to optimize fuzzy control in assisted living settings, specifically balancing energy efficiency and temperature stability, represents a new and practical approach. The structured pipeline of combining multiple algorithms allows for better handling of complex, multi-objective goals in real-world scenarios. The results highlight the potential of transfer learning to significantly improve energy optimization and occupant comfort in assisted living systems, where maintaining a balance between energy use and environmental stability is essential.

The paper is organized as follows: Section 2 addresses the flowchart and creation of triple flow of optimisation covering all three transfer learning combinations (GA → PSO, GA → NSGA-II, PSO → NSGA-II). Section 3 describe simulation results of 12 months of real IoT data, 12 months of generative data for energy consumption, 36 months generative database and also the discussion over data tables, respectively. Sections 4 shows our simulator results for analyse of variance and the optimized surfaces for datasets including visualisastion of Pareto Fronts. Section 5 contains the Conclusions and Future work.

2. Flowchart of Parallel Transfer Learning

The proposed flowchart targets two key objectives: energy conservation and maintaining ambient temperature stable, while increasing fan speeds can mitigate temperature deviations, it also increases energy consumption. Optimization Pathways include three parallel flows for different combinations, Fig. 1. The first optimization pathway explores transfer learning from GA to PSO, targeting both energy conservation and ambient temperature stability. The process begins with GA, which performs a global search across the solution space by analyzing inputs through a Fuzzy Inference System (FIS). GA identifies promising solutions for energy consumption and temperature control, leveraging fuzzy rules to balance energy use with environmental comfort. Once GA establishes a baseline solution, PSO takes over to refine it. PSO adjusts particle positions based on the global best and local best solutions, improving convergence speed and solution accuracy. This transfer learning process generates a new FIS surface that differs from those produced by GA and PSO individually. Finally, the pathway concludes with a variance analysis to evaluate whether the optimized solution meets the desired performance criteria for energy efficiency and temperature stability.

The second optimization pathway explores transfer learning from GA to (NSGA-II, focusing on balancing energy conservation and ambient temperature stability. GA initiates the process by performing a broad search across the solution space, analyzing inputs through a Fuzzy Inference System (FIS) to identify potential solutions for energy efficiency and environmental comfort. GA's exploration establishes a baseline solution, which NSGA-II then refines through multi-objective optimization.

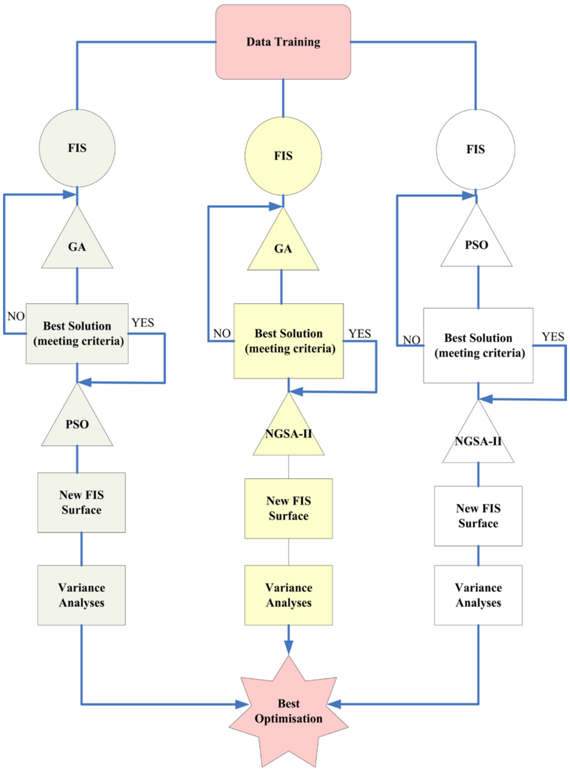

Fig. 1. Flowchart of triple pathways of transfer learning.

NSGA-II improves solution diversity and accuracy using non-dominated sorting and crowding distance mechanisms to maintain a well-distributed Pareto front. The pathway concludes with a variance analysis to assess whether the optimized solution meets the performance criteria for both energy efficiency and temperature control. The third optimization pathway explores transfer learning from PSO to NSGA-II, focusing on optimizing energy conservation and ambient temperature stability. PSO begins the process by rapidly converging to a promising solution through particle adjustments based on the global and local best positions. This enables PSO to identify a near-optimal solution for energy consumption and temperature regulation quickly. NSGA-II then refines this solution by enhancing solution diversity and accuracy using non-dominated sorting and crowding distance mechanisms to generate a well-distributed Pareto front. The pathway concludes with a variance analysis to confirm that the optimized solution meets the target criteria for both energy efficiency and comfort.

To enhance robustness, we integrate default sensor data into the Fuzzy Inference System, creating a training dataset based on real energy consumption data collected over 12 months. This setup ensures a fair comparison across optimization approaches by using a common dataset, consistent population size, and uniform generation count for all optimization paths. This standardized configuration allows for an objective evaluation of each optimization method's performance. The FIS of every step combinations is created using a Mamdani-type fuzzy system, which is one of the most common types of fuzzy inference systems, Fig. 2. In our research, we used three distinct datasets in our optimization process.

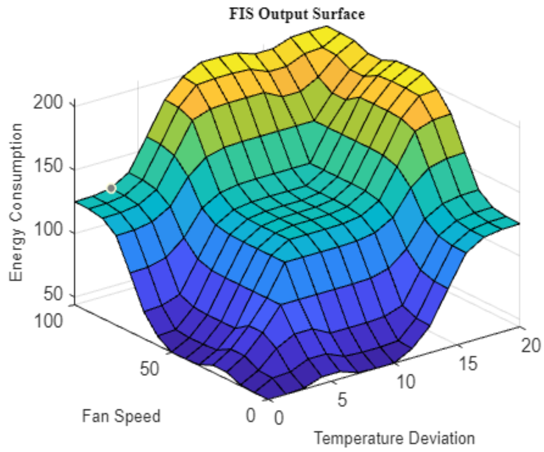

Fig. 2. Before Optimisation FIS surface.

The *first dataset*, which is the real data of IoT consistent across all optimization pathways and transfer learning combinations, serves as a common benchmark for evaluating the overall performance. The *second dataset*, which is generative data for simulations however, is specific to each individual pathway or flowchart, allowing for a more tailored analysis of the optimization process within each transfer learning combination. The *third dataset* is unique for each optimisation pathway but more extended to three years (36 months) of generative data. This approach ensures that each path is evaluated under conditions that reflect its unique characteristics, providing a comprehensive evaluation of each optimization strategy.

3. Simulations Results for Datasets

In this section, we present the simulations results based on two distinct data sources: a 12-months IoT data set for energy consumption selected randomly (Research Data-Dataset of usage pattern and energy analysis of an Internet of Things), [13], a 12-months and 36-months generative data last simulations used for testing the optimization algorithms behavior and trends.

3.1. Simulations of Real IoT Database

The first 12-month IoT data represents real-world energy consumption (kwatt from fans) data collected from sensors deployed in assisted living environments, providing a realistic foundation for evaluating energy efficiency. This dataset is used consistently across all optimizations approaches to ensure a fair and unbiased comparison, allowing us to measure the performance of each method under identical conditions by using the same IoT dataset for all transfer learning paths, we ensure that the comparison focuses solely on the efficiency and effectiveness of each algorithm, without the influence of differing data sources. We begin with first transfer learning as Table 1 from GA to PSO.

Table 1. Variance of Watt Consumed from GA to PSO.

IoT DATA (Month)	Energy consum	GA	PSO	GA to PSO
M.01	268	150	169	166
M.02	243	150	201	199
M.03	105	129	100	99
M.04	211	147	146	151
M.05	177	150	131	126
M.06	108	150	205	205
M.07	137	129	64	97
M.08	209	134	91	99
M.09	269	133	118	126
M.10	211	145	106	103
M.11	113	132	104	99
M.12	301	150	166	166
TOT	**2352**	**1699**	**1600**	**1637**

The first column represents the actual energy consumption for every month recorded from real-world data. The total real energy consumption is 2352, serving as a baseline for comparison against the optimization outcomes. The total energy consumption using GA is 1699, which reflects a 27.7 % reduction compared to the real consumption. This demonstrates that GA effectively explores the search space and identifies potential solutions for energy reduction, but its tendency to converge too soon to optimal limits affects its overall efficiency. PSO achieves a total energy consumption of 1600, reflecting a 32 % reduction from the real energy consumption. This suggests that PSO's ability to refine solutions through particle adjustments and swarm-based exploration leads to more efficient energy use than GA alone. The GA to PSO combination achieves a total energy consumption of 1637, reflecting a 30.4 % reduction from the real data. While this is slightly higher than PSO alone, the transfer learning process helps improve solution quality and velocity by enriching the results more effectively.

As the *second path* of transfer learning, we have chosen GA to NGSA. Since GA and NSGA-II share a similar nature as evolutionary algorithms, GA to NSGA-II transfer learning powers the global search capability of GA and the multi-objective optimization strength of NSGA-II. While GA explores the search space to identify possible solutions, NSGA-II refines these solutions by balancing multiple conflicting objectives, such as energy consumption as in Table 2. The total energy consumption using NSGA-II is 879, reflecting a significant 62.6 % reduction from the real energy consumption. NSGA-II outperforms GA significantly due to its ability to handle multi-objective trade-offs more effectively, as we mentioned in our previous work [1]. The GA to NSGA-II combination achieves a total energy consumption of 798, which reflects a 66.1 % reduction from the real data and outperforms both GA and NSGA-II individually.

Table 2. Variance of Watt Consumed from GA to NGSA.

IoT DATA (Month)	Energy consum	GA	NGSA	GA to NGSA-II
M.01	268	150	49	68
M.02	243	150	65	68
M.03	105	129	68	49
M.04	211	147	106	49
M.05	177	150	49	58
M.06	108	150	129	50
M.07	137	129	120	74
M.08	209	134	49	102
M.09	269	133	49	63
M.10	211	145	52	50
M.11	113	132	80	88
M.12	301	150	66	80
TOT	**2352**	**1699**	**879**	**798**

Furthermore, this combination is very fast in execution because NSGA-II benefits from the pre-explored solution space provided by GA, allowing it to converge quickly to an optimal solution.

As the *third path* of transfer learning we have chosen the optimisation from PSO to NGSA-II. PSO accelerates the initial convergence due to its fast exploitation of one desired objective function of the search space, meanwhile, NSGA-II improves solution diversity to the final solutions across multiple objectives that in our case are energy consumption and temperature deviation. The combined approach helps in avoiding premature convergence while improving the overall quality of the solution set as in Table 3.

The transfer learning combination of PSO to NSGA-II provides the highest reduction at 75.17 %. and this represents a 43.21 % increase in energy savings compared to PSO alone and a 12.54 % increase over NSGA-II alone.

Table 3. Variance of Watt Consumed from PSO to NGSA.

IoT DATA (Month)	Energy consum	PSO	NGSA	GA to NGSA-II
M.01	268	169	49	49
M.02	243	201	65	49
M.03	105	100	68	49
M.04	211	146	106	49
M.05	177	131	49	49
M.06	108	205	129	49
M.07	137	64	120	49
M.08	209	91	49	49
M.09	269	118	49	49
M.10	211	106	52	49
M.11	113	104	80	49
M.12	301	166	66	49
TOT	**2352**	**1600**	**879**	**584**

3.2. Simulations of Generative 12 Months Database

The second 12 months of generative data is different for every case of transfer learning. It does employ different generative data for each transfer learning combination, so we can evaluate how well each optimization method adapts to and performs under various data conditions, simulating different energy consumption patterns and challenges over time. In order to be fair in comparison we stimulate the three paths as above with the same consistency and same simulator. We begin with first transferring learning from GA to PSO as in Table 4.

Table 4. Variance of Watt Consumed from GA to PSO.

Gen. DATA (Month)	Energy consum	GA	PSO	GA to PSO
M.01	144	116	113	114
M.02	101	122	82	79
M.03	204	125	163	163
M.04	66	107	55	54
M.05	118	124	91	95
M.06	184	125	149	152
M.07	84	110	66	66
M.08	199	125	161	160
M.09	114	118	93	94
M.10	183	125	145	149
M.11	83	107	66	66
M.12	192	125	153	148
TOT	**1673**	**1429**	**1337**	**1340**

SO reduces energy consumption by 6.43 % over GA, while GA-to-PSO achieves a similar 6.23 % reduction. PSO is slightly more energy-efficient, but GA-to-PSO converges faster due to GA's strong initial exploration and the behavior is exactly as with real data. The next transfer learning path is same as we chose real data from Ga to NGSA-II, Table 5. NGSA reduces energy consumption by 17.63 % compared to GA, while GA-to-NGSA improves it further with an 18.30 % reduction. GA-to-NGSA performs slightly better because GA generates a well-diversified initial population, allowing NGSA to refine the solution more efficiently and converge faster. Final transfer learning for this type of dataset we explored the optimization from PSO to NGSA as in Table 6.

Table 5. Variance of Watt Consumed from GA to NGSA.

Gen. DATA (Month)	Energy consum	GA	NGSA	GA to NGSA
M.01	18	84	90	104
M.02	254	125	107	94
M.03	42	92	90	90
M.04	187	124	90	90
M.05	255	125	99	98
M.06	180	125	90	91
M.07	158	125	90	90
M.08	38	84	99	90
M.09	273	125	94	91
M.10	226	125	90	102
M.11	201	125	107	92
M.12	167	119	90	93
TOT	**2000**	**1377**	**1134**	**1125**

Table 6. Variance of Watt Consumed from GA to NGSA.

Gen. DATA (Month)	Energy consum	PSO	NGSA	PSO to NGSA
M.01	196	173	104	91
M.02	196	157	90	90
M.03	218	175	90	91
M.04	61	51	90	90
M.05	196	159	91	90
M.06	246	194	91	91
M.07	114	89	92	90
M.08	192	138	94	90
M.09	74	57	90	90
M.10	249	200	97	90
M.11	253	195	90	90
M.12	192	125	153	148
TOT	**2187**	**1713**	**1173**	**993**

PSO to NGSA shows the highest reduction in energy consumption 54.5 % compared to PSO. NGSA is also more efficient than PSO, with a 46.5 % reduction in energy consumption. PSO is slower compared to NGSA and PSO-to-NGSA. The transfer from PSO to NGSA accelerates convergence by refining the initial exploration provided by PSO, resulting in faster optimization and better energy efficiency.

3.3. Simulations of Generative 36 Months Database

Final approach we chose to explore is the 36 month generative data tailored to each specific combination of optimization algorithms. This database consists of synthetic data generated to mimic the dynamics of energy consumption over a longer period, providing more varied and extensive scenarios for each optimization path. This generative dataset is used to assess the flexibility and scalability of optimization methods, simulating longer-term trends and potential future behavior of energy consumption. It also provides more robust and thorough analysis of how the algorithms behave under different scenarios, ensuring the validity and reliability of the results. As showing the overall table with data it is out of the interest, we will only display results of three pathways of transfer learning exactly as approaches above in order to explore the behavior of optimisations as Table 7.

Table 7. Energy Consumption Comparison for three transfer learning pathways.

Optimizers (36 month)	Combin. 1	Combin. 2	Combin. 3
No FIS Optimized	5363	5896	5475
GA	4713	-	4468
PSO	4278	4691	-
NGSA	-	2340	2393
GA-PSO	4301	-	-
PSO-NGSA	-	1773	-
GA-NGSA	-	-	2387

As observed across all datasets analyzed, PSO to NGSA in Combination 2 delivers the highest energy reduction of 50.11 %, making it the most efficient learning transfer overall. This is followed closely by Combination 3 (GA, NGSA, GA-NGSA), which demonstrates slightly lower total energy consumption than NGSA alone. However, Combination 1 (GA, PSO, GA-PSO), while exhibiting a slightly less efficient performance compared to GA alone, stands out for its significantly faster execution time, a consistent trend across all datasets tested.

4. Analysis of Variance (ANOVA) and Optimization of Surfaces

In this section, we begin by examining the FIS surfaces as part of the first pathway in transferring learning from GA to PSO. The primary goal of this analysis is to assess how the transfer of knowledge from GA to PSO impacts the optimization surface, particularly in terms of energy efficiency and overall performance.

We first outline the key factors influencing the FIS surfaces, including the membership functions, rule sets, and their impact on the optimization process. Next, we analyze the resulting surfaces for both GA and PSO. The transfer learning approach, which adapts the FIS model initially optimized by GA to the PSO framework, is then evaluated in terms of its ability to refine the optimization process and achieve better performance. This analysis will help identify whether the transfer leads to improvements in energy consumption and overall system efficiency and will provide insights into how the learning from GA can be leveraged to enhance the PSO-based optimization process.

The first FIS surface optimized by GA alone over original FIS is shown in Fig. 3. As a global search method, GA is typically expected to explore widely, producing a surface with moderate roughness but good exploration of the search space. Meanwhile PSO can be smoother due to its particle interactions and exploration balance, Fig. 4. The PSO surface might show less roughness, especially in cases of well-tuned inertia and cognitive/social parameters. In the context of transfer learning, the GA to PSO surface can show a mix of GA's exploratory behavior and PSO's refinement. PSO narrows down the solution space explored by GA, resulting in higher solution density around optimal points and improved consistency, Fig. 5. GA identifies solution regions, and PSO enhances this by performing a more focused search within those regions, leading to optimal solutions closer to each other.

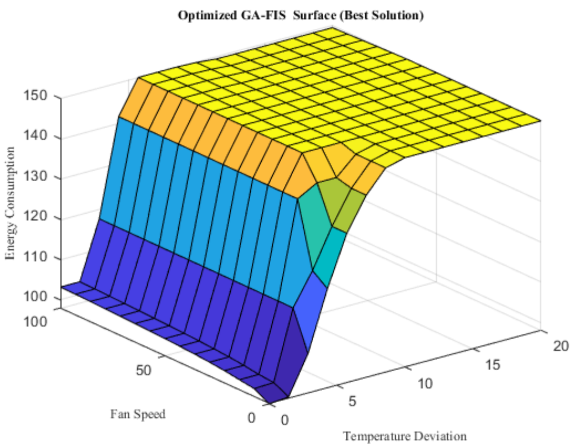

Fig. 3. GA Optimised FIS Surface.

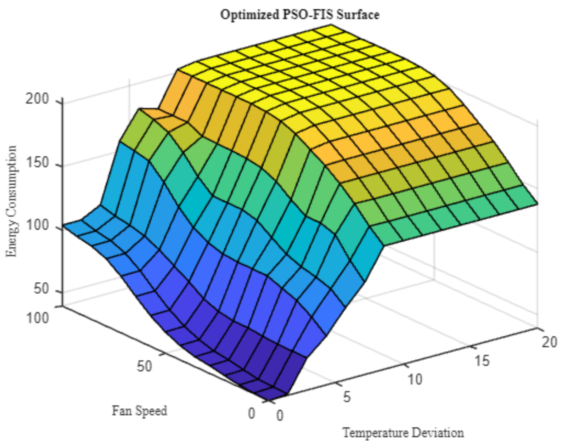

Fig. 4. PSO Optimised FIS Surface.

As a second path of transfer learning, we have chosen to explore the GA to NGSA. FIS surface by NGSA only as Fig. 6 shows smoothness and how gradually the objective function changes in the solution space.

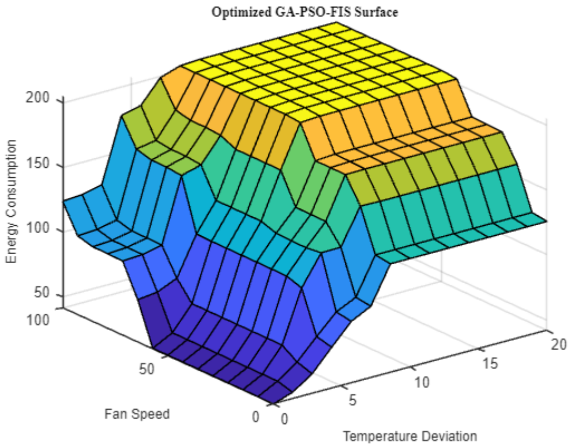

Fig. 5. GA to PSO Optimised FIS Surface.

A smooth surface is stable and easy to optimize, with unchanging improvements. As we can see due to its multi-objective nature, NGSA can have rough surfaces, especially in the beginning, as it searches for a diverse set of solutions. But in our scenarios, we transfer the best solution of GA to NGSA, and we have a smooth surface well from beginning as in Fig. 7. The surface is less rough because GA helps guide the search toward better starting points, reducing large fluctuations in the objective function.

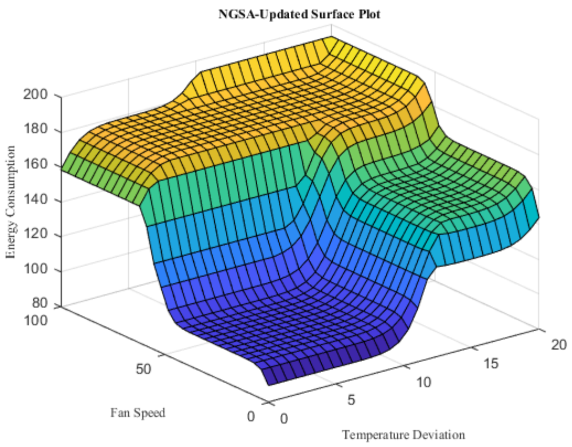

Fig. 6. NGSA Optimised FIS Surface.

One of the key advantages of GA to NGSA transfer learning is that NGSA helps to maintain diversity in the Pareto front, which is crucial for ensuring a better range of optimal solutions. By preserving diversity in this way, NGSA ensures that the final Pareto front is wider and more evenly distributed. This is important because it allows decision-makers to see a broader range of potential solutions, representing different trade-offs between objectives, and making it easier to choose a solution that best meets their needs as see in Fig. 8. In simpler terms, NGSA makes sure the solutions are spread out well across the front, rather than bunched up in just one area, which results in a better overall optimization. In the context of PSO to NGSA transfer learning combined with FIS, the optimization surface's roughness and smoothness evolve in a notable way. PSO alone exhibits roughness causin' the optimization surface to fluctuate, particularly in the early stages of the search, as particles explore the solution space, Fig. 4.

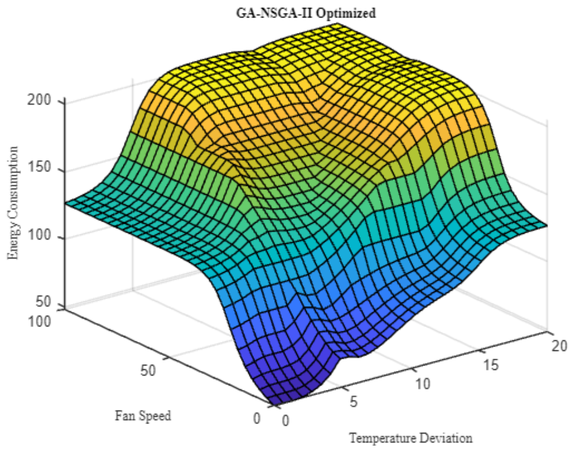

Fig. 7. GA to NGSA Optimised FIS Surface.

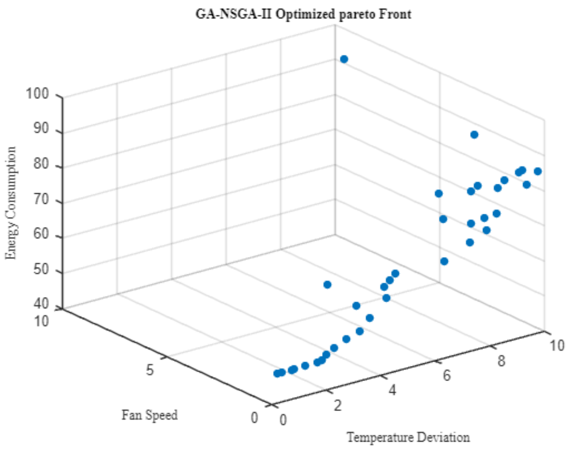

Fig. 8. Pareto front solutions for GA to NGSA.

However, when we apply transfer learning from PSO to NGSA, the process shifts. PSO first explores the solution space, identifying promising solutions, and then these solutions are passed to NGSA for further refinement. The optimization surface becomes smoother as NGSA fine-tunes the solutions, reducing the fluctuations observed in PSO's exploratory phase. This process results in a more stable surface shown in Fig. 9.

The Pareto front obtained from the PSO to NSGA-II transfer learning approach shows a broader and more evenly distributed spread, as illustrated in Fig. 10. This is due to NSGA-II's ability to maintain solution diversity and empower a well-balanced distribution along the front. By utilizing NSGA-II's non-dominated sorting mechanism and loading distance preservation, the approach effectively relives premature convergence and offers a more comprehensive exploration of the solution space. As a result, the Pareto front not only captures the trade-offs between competing objectives but also demonstrates a more stable convergence toward optimal solutions, leading to improved overall performance in balancing accuracy and efficiency.

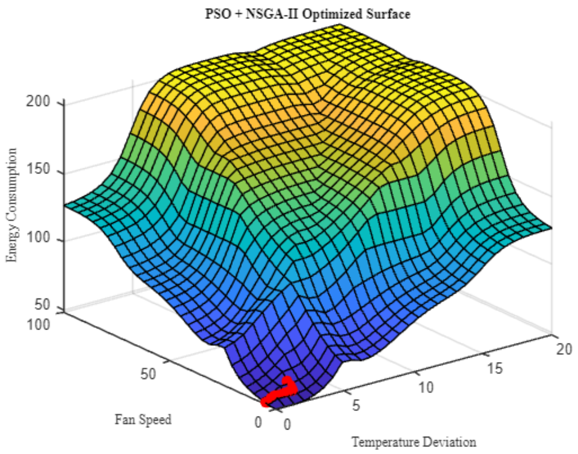

Fig. 9. PSO to NGSA Optimised FIS Surface.

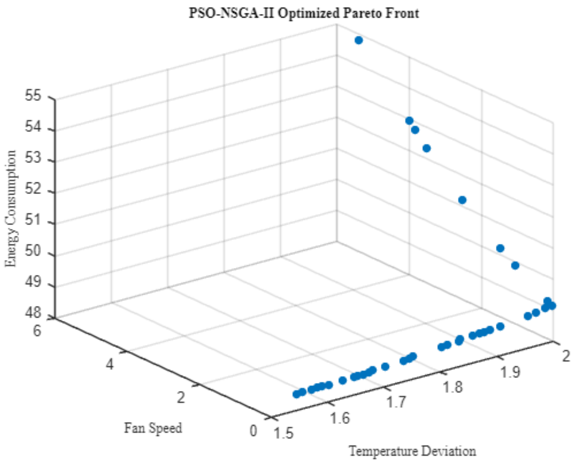

Fig. 10. Pareto front solutions for PSO to NGSA.

5. Conclusions

This research aimed to optimize energy management and occupant comfort in assisted living environments by using dynamic Fuzzy Inference System (FIS) controllers. At our best knowledge, most existing studies focus only on optimizing FIS controllers' parameters or improving the fuzzy rules and not using transfer learning to improve adaptability. The research focused on adapting the controllers to dynamic energy consumption patterns and occupant behavior through transfer learning techniques. Through the incorporation of transfer learning techniques such as GA to PSO, GA to NSGA-II, and PSO to NSGA-II we have shown that leveraging prior optimization experiences enhances the performance of FIS systems. The ability to reuse past optimization cycles significantly improves the adaptability of these optimizers, enabling them to respond more effectively to dynamic changes in energy usage patterns and occupant behavior.

Our results showed that using transfer learning from GA (Genetic Algorithm) to PSO (Particle Swarm Optimization) resulted in slightly lower performance compared to using PSO alone. However, the transfer learning approach was faster than PSO by itself. Even though the performance was a bit lower, the loss was minimal compared to the time saved. In terms of energy conservation, the small decrease in performance was not significant when considering the faster execution time, making this approach better for real-time applications where speed is important.

Meanwhile using NGSA after GA resulted in significantly better performance than using GA or NGSA alone. The execution time was faster, even outperforming GA while using the same number of generations and population size for a fair comparison.

The best performance in this study was achieved by transferring learning from PSO to NGSA. The ability to make real-time decisions using faster execution cycles is highly relevant for assisted living environments where rapid responses are crucial. This approach was highly effective in conserving energy, with energy consumption reduced to approximately half compared to energy conservation alone. The only drawback was the initial execution time for PSO, but once that step was completed, the transition to NGSA proceeded smoothly and efficiently, leading to significant improvements in performance without further delays. While there are challenges related to execution time, the results suggest that further improvements and optimizations in the transfer learning process could make these systems more adaptable and efficient in real-time applications.

Future work will focus on improving execution speed and exploring advanced optimization strategies to enhance the scalability and performance of energy management systems in assisted living environments. This includes developing a hierarchical FIS structure to enable multi-level optimization at both the individual room and building levels, ensuring more adaptive control. Additionally, NSGA-II maybe will be extended to handle many-objective optimization, incorporating inputs such as fan speed to balance complex trade-offs between energy savings, occupant comfort, and operational cost.

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