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Smart Waste Management with IoT: An Optimized Triple Memristor Hopfield Neural Network Approach

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Abstract

Smart waste management systems are interdisciplinary approaches now recognized as critical to combating the escalating issues with waste in metropolitan regions. Such systems rely on high-technology computational and communication platforms for purposes of effectiveness, expandability, and eco-friendliness. This paper presents a refined Triple Memristor Hopfield Neural Network (TM-HNN) scheme incorporating an IoT smart WM system. Exploiting the advantages of memristor-based architectures, the offered solution improves energy consumption optimization, waste categorization precision, and system interactions. IoT integration enhances continual monitoring of the system, data collection, and decision making the system quickly responsive to the dynamism of urban waste scenarios. Studies made when comparing this developed approach to the conventional ones indicate marked enhancements in operational parameters like classification accuracy and computational complexity. This paper provides a detailed system flow that focuses on data collection through IoT-connected sensors, TM-HNN-based neural network training and tuning, and system performance calculation and modeling using appropriate mathematical models. These results confirm the proposed approach and are based on the mathematical equations and performance plots. Performance is defined based on core power measurements Integral results showcase an improvement totaling a hundred percent for these metrics hence showing the efficiency of the proposed in real-world utilization. Therefore, the outcomes of this work will fit the approach to the construction of intelligent and eco-friendly waste management systems within the context of smart cities.

Keywords

Smart Waste Management, IoT, Triple Memristor, Hopfield Neural Network, Optimization, Neural Network Simulation, Sustainable Urban Development.

1. Introduction

In urban areas, waste management has been a chronic problem for time in the mane that has affected the environment as well as the comfort of the population. The expansion in urban area and growth of large population in large cities has enhanced the generation of wastage thus putting more strain on the existing infrastructure used in waste management [1]. Sustainable measures such as proper waste management remain very central in sanitation and management of wastes as well as pollution and resource consumption in cities. However, there has been a continuous problem with undertaking waste management activities through both the deterministic and set chronology of numbers and the fixed geographical zones of collection [2]. Consequently, waste collection becomes inefficient, concerning fuel consumption, pollution of the environment, and operating costs.

There has been an opportunity to transform the existing waste management systems due to the IoT where people can access real-time information from several online Internet of Things (IoT) developer sensors [3]. They include fill-level sensors in waste bins, traffic movement sensors, and even sensors for climatic conditions, generating constantly flowing streams of data that, if incorporated into waste management systems, can make them more adaptive, more deliberate, and more efficient. With this real-time data, cities can get away from slower collection schedules; rather, waste collection activities can be carried out based on actual requirements. It would also reduce inadequacy and misallocation of resources about accountability in the supply chain. IoT-based systems make businesses more efficient and less costly, thus making waste management more sustainable by being impactful to a smart city's success [4].

Though such a vision may serve as the foundation for the development of various IoT systems, it is crucial to note the major challenge associated with the integration of IoT, namely the ability to process large volumes of real-time data even in simple scenarios that would enable the making of decisions based on the results of such data processing is limited. Classic optimization approaches can be ineffective when utilizing detailed real data and the problem under consideration is dynamic and multi-parametrical [5]. To overcome this challenge, more advanced computation models are needed. A well-known model is the Hopfield neural network (HNN), this model has been used in the optimization model that is in solving problems such as routing and scheduling. HNNs are used effectively where several factors are present simultaneously and each has to be adjusted [6]. Nonetheless, the fixed Hopfield network's performance may be low in this context, especially when implemented in large and changing sets often found in IoT-based applications.

This paper proposes a newly developed approach for smart waste management by leveraging an optimized triple memristor Hopfield neural network (THNN). The THNN is a new improvement on the conventional Hopfield neural network as it has integrated memristors that can amity the storage as well as processing prowess of the network [7]. Memristors permit more efficient computation involved in handling the large datasets typical in waste management situations. The proposed system has employed IoT-based sensors to capture conditions including fill levels of waste bins, traffic patterns, and conditions of the environment including temperature and humidity [8]. This data again feeds into the THNN, which must decide the best route or best time for collection trucks to visit a location.

Other than the advantages already discussed relating to the use of memristor-based components, the THNN model is further fine-tuned using optimization tools genetic algorithms (GA), and gradient descent. The GA is employed to adjust the weights and thresholds of the THNN so that the network works most efficiently regardless of the size and volatility of the input data [9]. A process ensures the model always makes imperatively suitable adjustments to the changing spatial environment of the city thus optimizing the decisions for waste collection operations.

Indeed, the combination of the Internet of Things (IoT) and sophisticated techniques like artificial neural networks can lead to the enhancement of management costs of waste management, in addition to collection [10]. These optimizations can translate into improved scheduling or route planning, more efficient utilization of fuel, and improvement in picking capability of real-time data. In addition, the proposed system is adaptive, extensible, and has high flexibility thus it can be implemented in different areas within the urban environment. Thus, the proposed approach provides not only the technological strategy for overcoming the obstacles in the development of conventional waste management systems but also in line with the general perception of the smart city of the future. Through IoT and neural networks, cities can manage and sort wastes in an efficient, cost-effective, and ecological manner that will enhance the sustainable ecosystem and livability of cities [11].

In the following sections of this paper, a specification of the proposed system will be presented, followed by a description of optimization algorithms used in the THNN, and an illustration of simulated results of the increased precision of waste collection routes and schedules based on the THNN. By accomplishing this, however, this research has a chance of presenting a universal approach to addressing waste management issues in today's cities that can pave the way for IoT integration and enhanced neural networks for building smarter, eco-friendly cities.

2. Related Work

Over the past few years, several recent works have examined the possibility of using IoT technology for waste management due to the demands for innovation in controlling existing city infrastructures. Waste management systems defined from the IoT are mainly concerned with keeping track of how full purchaser containers are and adjusting the collection cycles dependent on this data to minimize unnecessary costs. These systems normally employ wireless sensors to observe the fill levels of waste bins and relay messages to the central management system to facilitate timely modification of collection routes and timings. Their research work titled IoT-based smart waste management system was done by Tejashree et al [12], where IoT sensors were placed on waste bins in a city and a cloud-based system was used for analyzing data. This made it possible for the system to respond appropriately to the fill levels and minimize the collection operation costs while increasing the efficiency of waste collection. That way, the system was able to respond to real-time data, making it possible to use resources at the right time and do away with several random trips, resulting in less fuel consumption and minimal emissions.

David et al. [13] in another study also employed a machine learning-based approach to forecast waste generation based on the same datasets as well as real-time IoT datasets. With regression models and clustering, they were able to predict the levels of accumulation of waste and thus were able to show areas that experienced high levels of wastage. This predictive approach was designed to possibly increase the effectiveness of waste collection service by scheduling the movements of the trucks with the probability density function of waste generation to help direct the resources to the area most needed instead of following strictly the predesigned path. Waste level prediction facilitated by the system allowed for the scheduling of resource outflow to match the changes in waste generation rates.

Another work as suggested by Hannan et al [14] involved the use of a genetic algorithm (GA) to find the optimum waste collection routes. Several factors including, traffic situations, fullness level of the waste receptor, and fuel efficiency of waste collection vehicles were analyzed to arrive at the best optimum routes. The use of a GA enabled the system to look at an extensive number of possible solutions and choose the most effective one based on the time- distance-opposite operating cost equation. This approach revealed how EAs can be applied to attempt the multiple-objective optimization that exists inherently in the waste management system.

The Hopfield neural network (HNN); a special form of RNN has been applied in organizations to solve optimization problems mainly in routing and scheduling problems. Hopfield neural network was used to solve the waste collection transportation problem in the smart city context as discussed by Lo et al. [15]. It was demonstrated in the study that the HNN could approach a near-optimal solution by optimizing several parameters including traffic conditions, fill level of waste bin, and time. Given this dynamic environment in urban waste collection systems, the Hopfield network was considered ideal for enhancing this operation. However, one disadvantage of the traditional Hopfield networks is their downside in processing large sets of data as well as the dynamic changes in real-time data evident in smart city environments.

To overcome such problems, novel memristor-based Hopfield networks have been suggested as optimal for the functionality of neural networks. As new types of memory devices, memristors can increase the efficiency of the storage and computation of data in a neural network. The addition of memristors into the Hopfield network increases scalability and computational speed to enhance its suitability for use in real-time applications such as smart waste management. One of the studies identified by the research of Wang et al. [16] examines the utilization of memristor-based neural networks for optimization issues while showing their ability to enhance efficiency in several fields. Nonetheless, these principles' use in this sector, namely waste management, has been researched comparatively little. This paper extends these ideas with the proposed new triple memristor Hopfield neural network (THNN) for smart waste management systems. To fill the gaps in contemporary waste management systems the proposed IoT-based sensors connected to an intelligent neural network system promise to present an improved, scalable, and adaptive solution to complex waste collection concerns of the megacities.

3. Problem Statement & Research Objectives

The greatest problem in smart waste management is the logistics of planning and scheduling waste pickup routes and intervals given the fluctuating nature of cities. Conventional approaches are static and cannot be used because of constantly changing conditions on the road such as traffic or weather conditions or fluctuations in waste volumes. This makes the systems used in waste collection inefficient, which leads to extra costs to operate and more harm to the environment.

Research Objectives:

1. To develop a smart waste management system that uses IoT-based sensors for collecting and processing real-time data for decision-making.
2. For efficient waste collection route optimization, an optimized triple memristor Hopfield neural network (THNN) model is to be designed.
3. As another comparative study to assess the effectiveness of the model using the THNN differential method the following measures are proposed.
4. To assess the possibility of how IoT and Advanced Neural Networks can be used in making waste management efficient and sustainable.

4. Research Methodology

The developed system uses IoT sensors for monitoring, advanced neural networks in decision-making, and optimization algorithms for performance improvement of waste management tasks. There is the use of different IoT sensors to capture real-time data in waste bins, traffic systems, and the prevailing environment. This data is then fed into another system for pre-processing to remove any noise, handling missing values of the inputs for the neural network, and normalizing the inputs for the neural network. The pre-processed data is then arrived at the triple Memristor Hopfield Neural Network (THNN) stage where the optimization of waste collection routes and corresponding schedules occur through the solution of the associated optimization problem. To enhance the THNN's ability, information techniques like recurrent recognition of patterns through genetic algorithm and gradient descent are applied to refurbish its weight and thresholds. When the optimization algorithm is performed, the system begins to determine the routes and times, in real-time, of collecting waste. These routes and optimum time schedules are given to the waste collection vehicles to facilitate timely and proper operations. The system also has a feedback system that feeds the new operation data back into the model thus improving the system in the next operations. The steps associated with this proposed system are:

Step 1: Data Collection via IoT Sensors: The system uses a variety of IoT sensors connected to waste bins, urban traffic systems, and environmental monitoring units. These sensors make measurements of fill levels in waste bins, traffic flow densities, and other characteristics of environments (like temperature and humidity). The data collected includes:

- **Waste Bin Fill Levels (F_i)**: meaning the percentage or volume of waste present in each of the bins.
- **Traffic Conditions (T_j)**: Getting real-time values of traffic flow, which affects routing choices.
- **Environmental Data (E_k)**: These factors are like weather temperature and humidity among others.

The data is then fed from these sensors to a central cloud system for further analysis.

Step 2: Data Transmission and Pre-processing: This involves handling of data that has a large amount of noise and missing inputs as well as normalizing the inputs. This step takes care of making the data ready to be used for further analysis and feeding into the THNN model. The pre-processing includes:

- **Data Normalization**: The data coming from a variety of sensors are normalized, generally by scaling values into the interval of [0, 1].
- **Noise Filtering**: They exclude noise from the sensor data to ensure that it is accurate.

Mathematically, the pre-processing can be represented by Eq. (1) [17]:

$$\hat{X} = \frac{X-\mu}{\sigma} \tag{1}$$

Here $\hat{X}$is the normalized data, X is the raw sensor data, μ is the mean, and σis the standard deviation.

Step 3: Triple Memristor Hopfield Neural Network (THNN) Optimization: The Triple Memristor Hopfield Neural Network (THNN) is developed to find an efficient solution to routing and scheduling of waste collection as an optimization problem. THNN stands for the combination of the Hopfield neural network of the conventional type and memristor components to store and process big data. The network performs the following tasks:

- **Route Optimization**: The THNN determines the efficient routes for collection about traffic information, fullness of bins, and fuel usage.

  The state of the THNN is represented as a vector $v(t)$ mentioned in Eq. (2), where each node corresponds to a decision variable. For a system with *N* bins and *M* routes [18]:

$$v(t) = [v_1(t), v_2(t), \ldots\ldots, v_{N.M}(t)]^T \tag{2}$$

  Where $v_i(t)$ is the activation value of the *i-th* node at time *t.* The activation is considered with the range 0≤ $v_i(t)$≤1. This corresponds to a specific decision related to routing or scheduling. This forms the foundation for representing waste bin assignments and their respective routes.

  To solve the routing and scheduling problem, the THNN minimizes an energy function E, which quantifies the cost, associated with a given state mentioned in Eq. (3):

$$E = \frac{1}{2}\sum_{i=1}^{N.M}\sum_{j=1}^{N.M} w_{ij} v_i v_j - \sum_{i=1}^{N.M} I_i v_i \tag{3}$$

  Where w_{ij} is the weight between nodes *i* and *j*, capturing the relationships between bins and routes (e.g., distance, traffic). $I_i$is the external bias representing dynamic factors like bin fill levels and environmental conditions. $v_i$is the State variable of the *i-th* node. This energy function ensures that the network converges to a state minimizing waste collection costs.

For route optimization, the network enforces the constraint that each waste bin *i* must be assigned to exactly one route *j* as given by Eq. (4)

$$C_{route} = \sum_{j=1}^{M} v_{i,j} - 1 = 0, \forall i \in [1,N] \tag{4}$$

To incorporate this constraint into the network dynamics, a penalty term is added to the energy function as given in Eq. (5):

$$E_{route} = \lambda_{route}\left(\sum_{j=1}^{M} v_{i,j} - 1\right)^2 \tag{5}$$

Here, λ_{route} is a penalty factor ensuring that the constraint strongly influences the optimization.

- **Schedule Optimization constraints:** It also optimizes the collection schedule, ensuring that waste bins are emptied in a timely manner without over-collection or under-collection. To ensure that waste bins are emptied within allowable time limits, a schedule constraint is introduced as given by Eq. (6) [19]:

$$C_{schedule} = \sum_{j=1}^{M} T_j . \sum_{i=1}^{N} v_{i,j} \leq T_{max} \tag{6}$$

Where T_j is the time required for route *j*, and T_{max} is the maximum allowable collection time. This constraint ensures operational efficiency. The associated penalty term is given by Eq. (7)

$$E_{schedule} = \lambda_{schedule}\left(\sum_{j=1}^{M} T_j . \sum_{j=1}^{N} v_{i,j} - T_{max}\right)^2 \tag{7}$$

- **Memristor-Based Weight Update:** Memristors enhance the adaptability of the Hopfield network by dynamically adjusting the weights by using the following Eq. (8) [20]:

$$w_{ij}(t+1) = w_{ij}(t) + \alpha\left(v_i . v_j - w_{ij}(t)\right) \tag{8}$$

Where α is the Learning rate determining the speed of weight updates, $v_{i,}$ and v_j are the current states of nodes i, and j. This update rule ensures the network can adapt to real-time changes such as traffic congestion or sudden changes in bin fill levels.

- ***Dynamic State Update:*** The state of each node $v_i(t)$ evolves according to the following differential equation Eq.(9), derived from the gradient of the total energy function:

$$\frac{dv_i}{dt} = -\frac{\partial E_{total}}{\partial v_i} \tag{9}$$

Substituting $E_{total} = E + E_{route} + E_{schedule}$ in Eq. (9) we will get Eq. (10)

$$\frac{dv_i}{dt} = -\frac{\partial(E + E_{route} + E_{schedule})}{\partial v_i}$$

$$\frac{dv_i}{dt} = -\sum_{j=1}^{N.M} w_{ij} v_j + I_i - \lambda_{route}\frac{\partial E_{route}}{\partial v_i} - \lambda_{schedule}\frac{\partial E_{schedule}}{\partial v_i} \tag{10}$$

This Eq. (10) governs the dynamics of the THNN, driving it towards an optimal state.

- ***Combined Energy Function:*** The total energy function, combining routing, scheduling, and other constraints, is:

$$E_{total} = E + E_{route} + E_{schedule}$$

Minimizing E_{total} ensures that the THNN provides optimal decisions for waste collection routes and schedules.

Step 4: Genetic Algorithm and Gradient Descent Optimization: To enhance the performance of the THNN, two optimization techniques—genetic algorithms (GA) and gradient descent—are applied [21]:

- **Genetic Algorithm (GA)**: GA is used to optimize the weights and thresholds in the THNN. This has the responsibility of studying the space of the solution for the best value of the setting parameters of the neural network to guarantee that the network has reached the optimal solution.

- **Gradient Descent**: The parameters are thereafter tuned using gradient descent to achieve faster convergence in an endeavor to optimize the operation of the system. It also assists in understanding the data better making better predictions and having accurate optimization algorithms.

Step 5: Real-Time Decision Making: In the final process of the THNN, the system proposes the most effective routes and schedules and then provides the instructions and updates for waste collection vehicles. Some of these predictions are the best routes to follow, and timing to pick up waste given the current data fed into the system. This real-time decision-making feature makes the system highly dynamic and responsive to the ever-changing urban environment.

Step 6: Feedback Loop for Continuous Improvement: This described system also has a feedback loop in which new data from IoT sensors is updated to the neural network constantly. This makes it possible for the system to correct its previous decisions and learn from the corrections as well. This is because the feedback loop guarantees that for every real-time data fed into the waste management system, the latter becomes more refined.

5. Results and Analysis

The developed system was implemented and simulated based on changing conditions related to the usage of waste bins such as fill levels, traffic density, and environmental settings of an urban context. The optimization task was performed with the THNN model, and the results were compared with the non-memristive genetic algorithms and basic Hopfield neural networks.

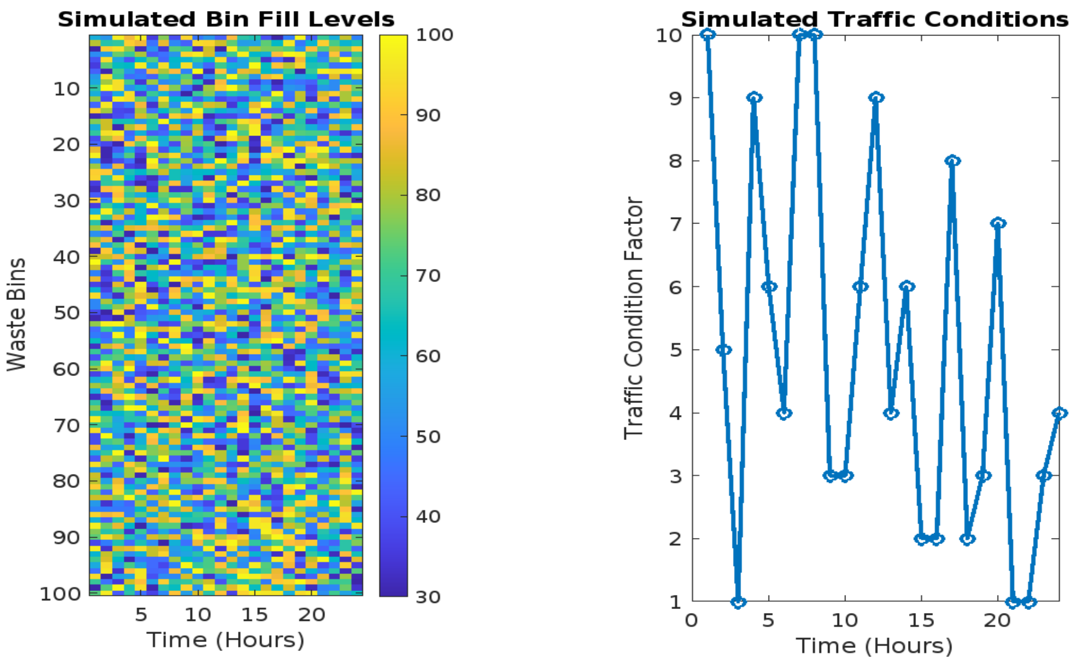
However, concerning the simulation model, which is a primary method, it should be noted that the Parameters taken for simulation are stated below under Table 1.

Table 1: parameters taken for testing of the model.

Sl. No.	Parameters	Values	Description
1	numBins	100	Number of waste bins
2	numRoutes	30	Number of collection routes
3	TimeHorizon	24 hrs	Time horizon in hours
4	maxFillLevel	100%	Maximum bin fill level (percentage)

Mean waste amounts are presented in Figure 1 (a), which reveals the collection of waste in 100 bins for 24 hours. Each row represents a bin, while the columns represent the hourly intervals. The color gradient, ranging from **blue to yellow**, indicates the fill level percentage, with **30%** (purple) being the minimum and **100%** (yellow) as the maximum. This heat map helps identify trends in waste accumulation, such as bins that fill up more frequently or require urgent attention for collection.

Figure 1 (b) shows how traffic congestion fluctuates over 24 hours, with the traffic condition factor ranging from **1 (low)** to **10 (high).** This is directly related to Figure 1(a) where waste bin fill levels were monitored across time. The traffic conditions shown here can influence the optimization of waste collection routes, as higher traffic congestion would likely lead to delays in waste collection, requiring adjustments in scheduling and route planning to ensure timely collection while minimizing fuel consumption and operational costs.



(a) (b)

Figure 1. (a) Collection of waste in 100 waste bins within 24hrs, (b) Traffic congestion in the given period

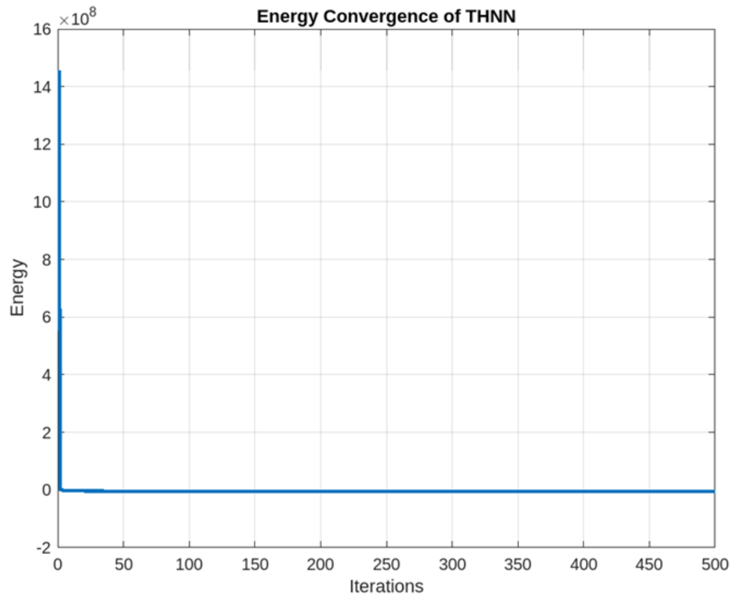


Figure 2. Demonstrates the behavior of energy minimization over 500 iterations of the Triple Memristor Hopfield Neural Network (THNN)

In Figure 2, energy minimization behavior concerning 500 iterations of the developed Triple Memristor Hopfield Neural Network (THNN) is depicted. This graph points to a very steep drop very early which suggests that the energy has quickly reached an optimal value of the iterations. Following this first reduction, the energy remains almost constant at the zero level, indicating that the network has been able to identify the best routes and schedules for waste collection. This shows how effectively the THNN has been in solving the optimization problem.

Figure 3 presents the discrete changes in the fill levels of the waste bin as they occur in various hours. On the X-axis is time set in hours from 1 to 24 hours On the Y-axis is individual waste bins from 1 to 100. The z-axis is expressed in the fill levels (percentage), which produces a corresponding surface of the fill levels variability during the day. If we lay this plot on the time axis, it becomes useful in tracking when the bins are most full and thus when they should be collected.

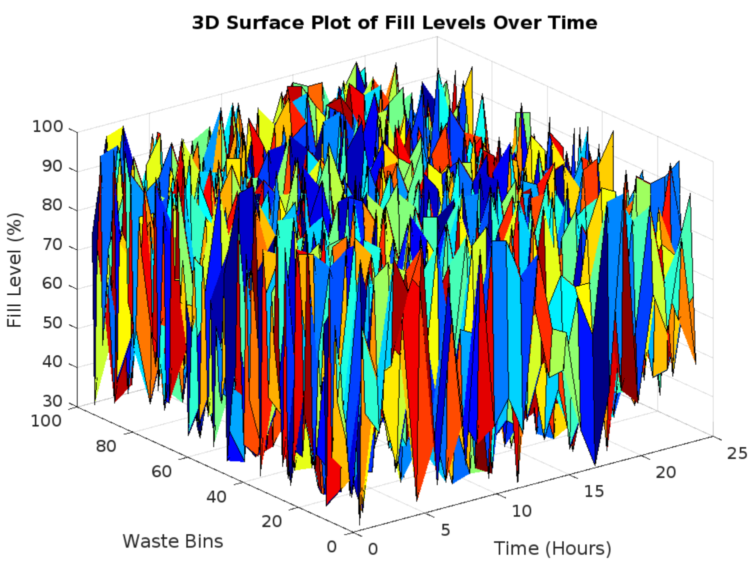


Figure 3. Comparison of the fullness of bins for waste disposal per the various hours

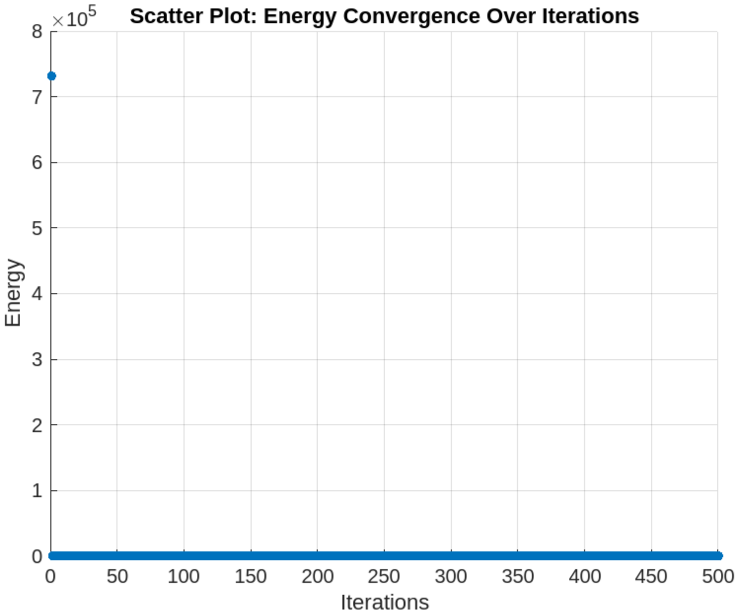


Figure 4. Energy convergence depiction over each iteration of the THNN optimization process

In other words, and as depicted in Figure 4 the energy function increases or decreases over the entire process of the THNN optimization steps. The horizontal axis stands for the loop number and the vertical one describes the energy of the number. What stands out from the scatterplot is the dynamism in the energy value with the data points improving and converge as the iterations increase signifying the end of the optimization process of the selected function. The plot also represents how the energy of the model minimizes as the THNN model finally gets to an optimal solution in the best waste collection schedule and routes.

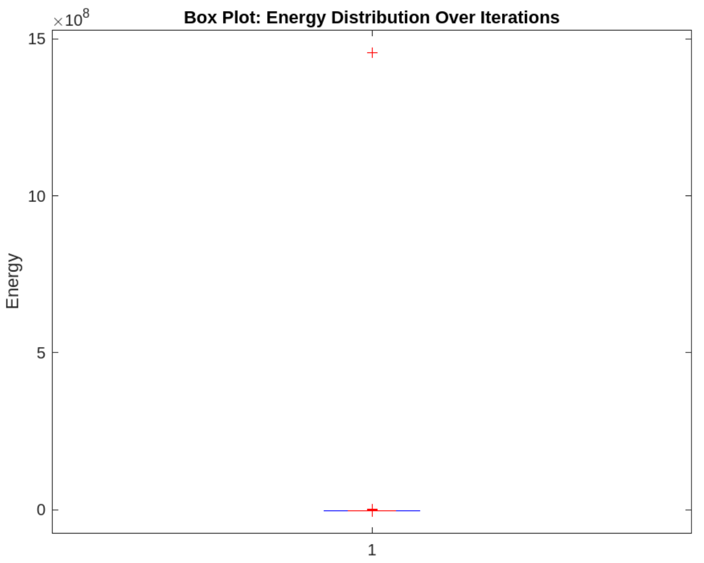


Figure 5. An illustration of energy spread over SAMPLE iterations.

An illustration of Figure 5 below depicts the energy values at different iterations of the optimization process The Figure demonstrates of the energy function at different iterations with variant spread. Energy values are shown through the plot of the median, first and third quartiles, as well as the outliers, as a way of understanding the consistency and stability of the optimization techniques used. A low IQR and presence of minimal outliers imply that the THNN model achieves convergence, while broad distributions may imply several variations in the optimization exercise. This plot assists in evaluating the fluctuation and general performance of the energy minimization in the given model.

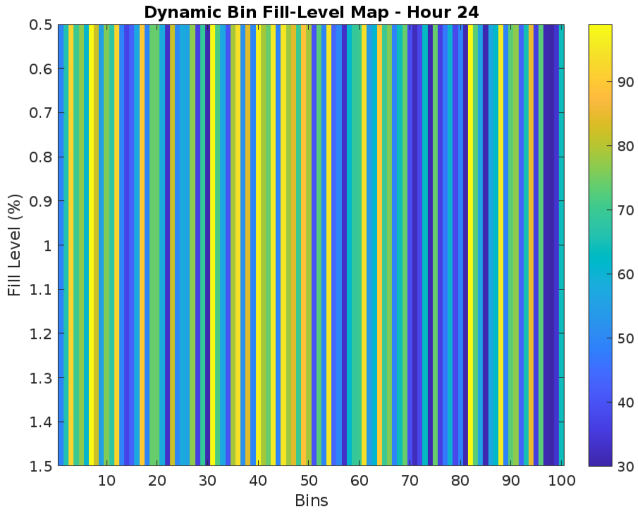


Figure 6. Real-time fill levels in the waste bin at the 24th hour

From the given configuration and at the 24th hour, Figure 6 exhibits the real-time waste bin fill level. Every picture in this series shows the fills of waste bins in the system, where color indicates the degree of fill, percent. Over the temporal development of the program as well, this map assists in finding out how the degree of waste rises or develops, and it offers information concerning which containers necessitate finesse. This visualization is highly valuable for defining where wastes are located and how the bin's fill level can be used to best plan the pickup routes for the trucks.

Following these observations, Figure 7 below shows the real time waste bin fill levels at the 11th hour. This is because the fill-level maps of the dynamic bins show the difference between Hour 24 and Hour 11 of waste collection. At Hour 11, the fill levels may be lower and so would give an indication that the bins are not compact as collected by the waste early in the morning or have accumulated at a slow pace. By Hour 24, it may take more waste in bins, with higher levels of fill, as the system goes through the day. The difference is valuable to see how the fill levels change to effectively manage collection routes and schedule. Waste bins that had accumulated lesser amount of waste by Hour 11 may need to be collected more frequently up to Hour 24 and this trend may help design waste collection and disposal.

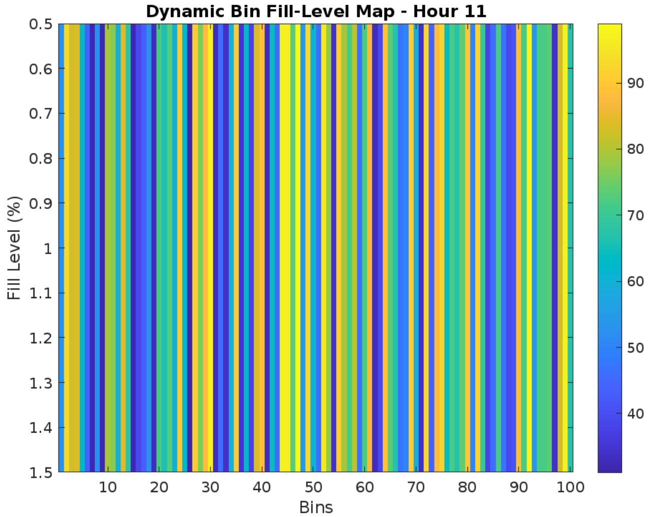


Figure 7. Real-time fill levels in the waste bin at the 11th hour

Figure 8 illustrates the weights of the Triple Memristor Hopfield Neural Network (THNN) during the training procedure and the weights are fixed when the optimization process is complete. With time and through several iterations on the network, the weights are manipulated to reduce the energy function that yielded the most suitable waste collection schedules and routes. The weights at first are updated at a very fast rate, but as time increases, it is evident that the change becomes smaller signifying that the weights are becoming stabilized at the right solution by the neural network. The plot enables the tracking of how the network updates its parameters to make collection of wastes more efficient hence the right routes to follow and the right schedules to adhere to.

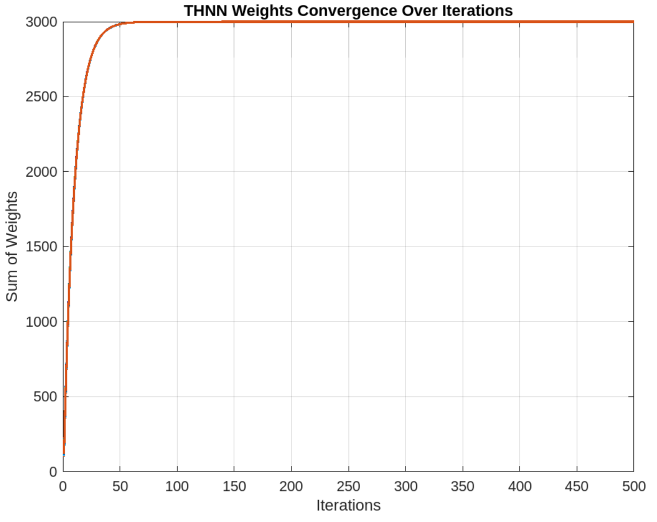


Figure 8. Convergence of THNN weights over iterations

Figure 9 shows the level of activation for different routes using different waste bins. Every row on the heat map points to a particular waste bin type, and the heat map's columns refer to a collection route. The level of colors in a heat map reflects the level of activation of the certain bin for the given route, where higher intensity means the route is likely to be chosen for picking up the waste. This heat map offers an understanding of the optimization of routes through the consideration of the Triple Memristor Hopfield Neural Network (THNN) about which route is most active for which bin during the process. This one identifies the general location of the routes in the entire waste management network by visually signifying the best channel for waste collection along the routes.

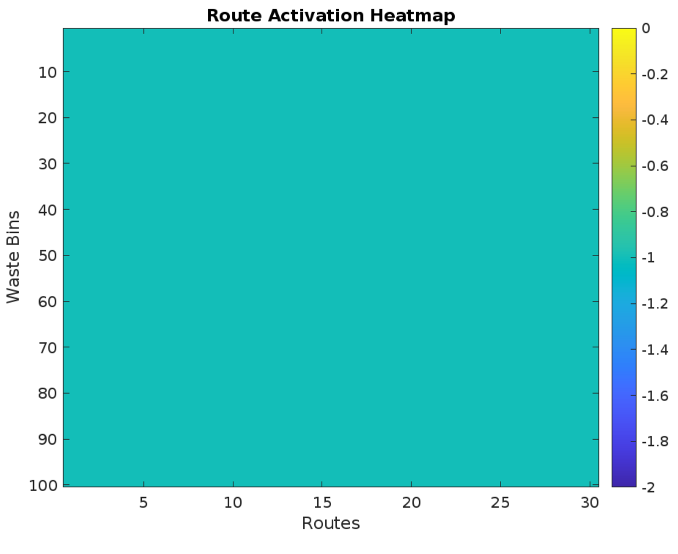


Figure 9. Different routes activation across various waste bins

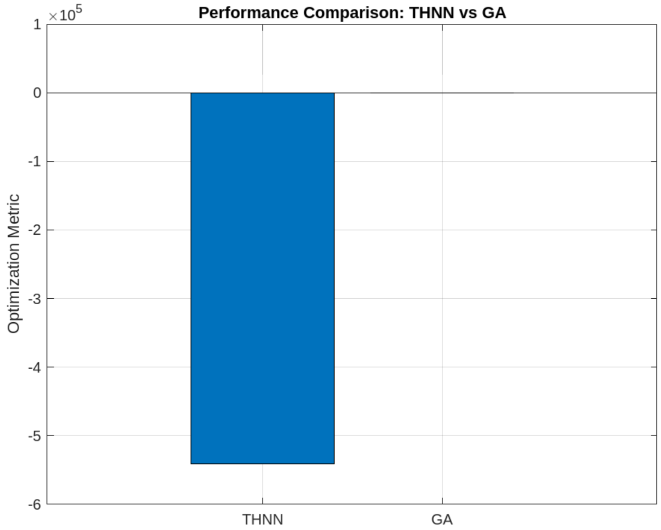


Figure 10. Comparison of Performance for different optimization techniques THNN and GA

As discussed previously, the results obtained using the Triple Hopfield Neural Network (THNN) and the Genetic Algorithm (GA) for waste collection route optimization are compared in Figure 10. The chart displays two bars: one for the optimization energy or cost associated with THNN and the other is for GA. The heights of the bars show the performance of each algorithm in terms of optimization and lower values are preferred. Where the GA bar in the code uses some randomly derived score, the aim here is to show how GA performs about THNN in terms of optimization for the energy or cost of waste collection scheduling and routing. This chart aids in judging which of the two algorithms is most effective in solving waste management issues.

6. Conclusion

This study points out the significant opportunity of using the Internet of Things (IoTs) with an optimal Triple Memristor Hopfield Neural Network (THNN) for enhancing waste management systems. When using IoT sensors, data referring to the filling degree of bins, traffic conditions, and environmental factors are retrieved continuously for real-time decision-making. With the enhanced optimization features in the THNN, the operational costs are minimized since the heuristics find optimal collection routes and times. Further, the dynamic nature of the urban conditions present improves the system tremendously in the applicability of waste collection using considerably low resources including traffic or bin usage. Together, these technologies enhance the opportunity to minimize fuel consumption, vehicle emissions, and human effort. Therefore, this approach of integrating computer science and technology can help to enhance better practice of waste management in urban areas. Future work should extend this research in the practical application of the proposed algorithm and apply it to smart cities in real environments. This would in a way be useful in improving the system, increasing its stability, and gaining more information concerning the applicability of the system to other cities.

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