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ENERGY OPTIMIZATION OF THE MULTI-OBJECTIVE CONTROL SYSTEM FOR PURE ELECTRIC VEHICLES BASED ON DEEP LEARNING

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Abstract. Advancements in information technology have revolutionized multiple sectors such as healthcare, industrial control, and environmental monitoring. With the advent of smaller, more sophisticated and wireless sensors, their applications have expanded across various industries. These sensors offer numerous advantages like cost-effectiveness, easy setup, reliable transmission, and high capacity for data processing. However, despite their benefits, there are certain limitations to consider. The primary constraint that affects their lifespan is energy availability, as replacing or recharging power sources for nodes can be challenging or infeasible. The reliance on batteries hampers data analysis by network nodes, hindering the exchange of information. Hence, prolonging the network's overall lifespan is crucial for optimizing its performance. The existing approaches, with their tried-and-tested practices and heterogeneity, require enhancements to address specific characteristics. In every application, two critical aspects are the duration of network operation and energy consumption for data routing. Through comparative analysis, it is evident that various algorithms and techniques can reduce energy usage to different extents. Based on these findings, a recommended strategy is to achieve a significant 70% reduction in energy consumption.

Key words: Aggregated data energy balance, mobile detector, info linkage.

1. Introduction. Sensors are compact devices with communication and interaction functions, playing a crucial role in various application fields. They are usually equipped with WiFi communication components, allowing them to not only sense the surrounding environment, but also transmit data and interact with other devices. This versatility makes sensors widely used in monitoring, control, and data acquisition, providing critical support for modern technology and automation systems [4]. However, due to the limited power capacity of each sensor, managing their energy consumption becomes crucial, especially considering that these sensors often operate in remote or challenging environments, such as frontline areas or vacant plots. Consequently, it becomes necessary to replace the batteries of sensors located in significant local regions where numerous sensor nodes are densely deployed (up to twenty nodes per square meter). Developing an approach that can adapt the local sensor infrastructure without compromising the overall system's performance becomes vital, considering the aforementioned attributes of sensors. The majority of the plans do, however, take strength preservation into consideration. The direction-finding task is then formulated as a simple coding issue [7], and a cost-directing set of rules is then given, mostly based on link pricing. The resilience of the sensor network and the boundaries of what may be observed are the sole foundations of the suggested architecture for data alliance security. It will investigate which channels the MPMC rule set uses in a specific area. The results of the tests indicate that the placement of this rule is least comfortable with the sum of standard data.

Production and energy consumption are significant factors in domestic and global strategic choices. The short- and long-term sustainable development as it is intended in various countries must be closely monitored [8]. The meta-heuristic algorithm is one of the cutting-edge techniques and algorithms used in this prediction. Meta-heuristic algorithms can minimise errors and standard deviations when processing data. It is possible to analyse uncertainty and find any defects in the datasets using a variety of statistical techniques. Both the exponential and linear models employ each technique. The extent of error is about 3.7%. The winning model predicts that by 2030, global energy consumption would be at 459 terawatt-hours. Electricity-producing industries may be able to make erroneous predictions about future energy use thanks to meta-heuristic algorithms. To reduce this inaccuracy and produce a more accurate prediction, researchers should use various methods. Efficient energy management is essential for a nation's growth and development. Especially in the twenty-first century,

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electricity is one of the most significant energy sources. One may forecast electricity generation by calculating the output of existing power plants and speculative development projects [15].

Predicting power consumption, however, is a very challenging situation. There are both conventional and cutting-edge techniques for forecasting electricity usage. Prediction errors have been reduced thanks to contemporary techniques like neural networks and meta-heuristic algorithms. This article examined the IRO, CBO, and ECBO meta-heuristic algorithms, and six models were created. Two linear and one exponential mode were among the three methods used in these models. Calculations were based on the linear model of the ECBO algorithm, which had the smallest error of the six models. The Mean Absolute Percentage Error (MAPE) for the winning model was 3.7%. The trend of increasing power usage was estimated through 2030. 2030 will see the use of electricity reach 459 terawatt-hours. Four socioeconomical criteria have been taken into account to predict power usage. These four elements are the GDP, the population, the cost of electricity, and the consumption rate from the previous year. It is possible to plan for the country's power grid and important developments by using meta-heuristic algorithms and reducing the forecast error. By contrasting the results of several meta-heuristics, researchers might reduce this error level.

The authors of this study advise managers in the power generation sector to employ cutting-edge forecasting techniques like neural networks and meta-heuristic algorithms. Using unique meta-heuristic algorithms to address the proposed scheduling problem is advised since precise solution methods. At the same time, they can generate optimal answers in more execution time and need help analyzing large-scale issues and solving them logically. Additionally, MOKSEA algorithm performs substantially better than MOKA. Moreover, MOKSEA is acknowledged as the top approach for solving problems in the RAS, SNS, SM, and NPS indices. This study has offered some valuable managerial insights. One of the most crucial elements is that figuring out the best production schedule is very challenging. Additionally, there are frequent updates to this schedule. Therefore, finding a suitable solution quickly and within reason is essential by utilizing novel approximation techniques while considering numerous constraints [5, 1].

2. Literature Survey. According to the research results of coverage evaluation standards, the proposed technology shows significant advantages in terms of coverage, increasing by 12% compared to the FGOA method, 15% compared to GOA, and 16% compared to GSO. These data indicate that this technology has the potential to improve network coverage and can bring better performance to IoT systems. The Internet of Things (IoT) is a complex heterogeneous system that combines various communication technologies with data recording programs to collect, transmit, analyze, and store data. In the Internet of Things, edge nodes, such as RFID tags or sensor nodes, collect data through the network layer and transmit this data to customers or service providers. To achieve this goal, effective allocation of resources is crucial. By improving the performance of edge nodes and improving the service level provided by the network layer, the overall service cost can be reduced. This is crucial for the sustainability and service quality of the Internet of Things. However, further research is still needed to address the issues of network durability and service quality related to the Internet of Things. This will help ensure the stable operation of the Internet of Things system and provide high-quality services to meet the growing demand [14].

Most Internet of Things applications use distributed nodes with restricted power sources. As a result, it is urgently necessary to develop new techniques to stop energy loss, which reduces networks' lifespan. Due to these restrictions and the high network node density, designing and managing wireless networks has become difficult. All layers of the network protocol stack now require energy awareness. For instance, we urgently need to determine how to employ energy efficiency at the network layer to select paths and transmit data. IoT routing has grown in relevance and significantly impacts lowering energy usage, making it a significant research challenge. Energy-efficient routing is one method for reducing the amount of energy needed by selecting the best path. Three criteria were used to assess the effectiveness of the suggested method: network life, coverage rate, and residual energy [3].

Calculated optimization can be an effective way to reduce power consumption when working with low-energy buildings. This paper provides a strong combination strategy based on the bird of paradise optimization algorithm (POA) and one contender optimizer (SCO) to address issues with building energy optimization. The suggested hybrid algorithm (POSCO) makes use of the local solid search capability of the single candidate method and the efficient global search capability of the pelican upgrade. To optimize the building, the optimization technique was developed and integrated with the most recent edition of the Energy codes [13, 11].

The findings show that the POSCO technique outperforms a few cutting-edge methodologies and reduces building energy consumption at specific temperatures and lighting conditions. POSCO is contrasted with other algorithms, such as basic POA. In light of the information, The findings of the building energy optimization procedure for various climates demonstrate that modifications to the meteorological data did not considerably impact the efficiency of the process. This work presented a hybrid optimization technique based on the single candidate optimizer (POSCO) and pelican optimization to evaluate buildings' most minimal energy use. The strong exploratory capability of pelican optimization and the efficient local search capability of the single-candidate approach is used in the suggested methodology. Several unimodal and multimodal benchmark functions are used to evaluate the performance of the proposed method.The results demonstrate that POSCO outperforms conventional POA and other techniques in identifying the overall solution. The suggested solution outperformed other approaches in determining the global best for seven of the thirteen functions taken into account. It also resulted in better outcomes for the other functions. Each optimizer's performance has been unaffected by the change to the weather file. POSCO is a viable candidate method for BEO models because, in accordance with the outcomes of the competition simulation, it can accurately and dependably forecast the best design.

3. Materials and Methods.

3.1. Description of the genetic algorithm. The biological algorithm (GA), an evolutionary efficiency technique, has been successfully used in engineering. In this organized yet randomized search, mutation, crossover, and selection are handled by genetic operators. The core concept of GA includes the following key points: 1.Population: Firstly, GA will create a population consisting of multiple individuals, each representing a potential solution. 2.Selection: GA uses selection operations to evaluate individual adaptability, usually measured through a fitness function. The adaptability function evaluates the quality of each individual's solution in the problem space. Then, based on the size of adaptability, individuals who are more conducive to problem-solving are selected as parents. 3.Crossing: Selected individuals (parents) can generate new individuals (children) through crossing operations. Cross operation simulates the process of gene recombination in biology, by combining the chromosomal parts of two or more individuals to generate new ones. 4.Mutation: In some cases, GA may introduce mutation operations to introduce new randomness into the population. This simulates the process of gene mutation in biology, which helps to explore a wider range of problem spaces. 5.Iterative evolution: GA repeats the above steps for multiple generations, each generation generating new individuals. As algebra increases, better solutions have a higher chance of being preserved and passed on to the next generation. Let's look at a couple of jargon. A term that refers to genetic algorithms. The first suggested solution to the issue involves chromosomes. The genes or alleles on each chromosome must be the same size. Selection. The fundamental genetic process transfers genomes with greater quantity to the following generation. Position, constant state, and the gambling ball are other selection strategies in addition to elitism. Any selection method could be used, depending on the requirements of the application. Crossover. When a pair of adult genomes is chosen for bridging and some of their DNA is transported across, the chromosomes of the offspring are created [16]. 100,000 | 001,000 on the first chromosome.

Chromosome 2:... 000,100 | ... 001...

1... 100,000 | 000,001 offspring

2 offspring were born, 000,100 | 001,000....

How exercise serves a purpose. Chromosomes with more excellent fitness scores would result in more offspring than those with fewer points, according to the fitness function, which estimates these values. This article's health rating is the sum of every one of its components multiplied by the stated component proportion. Mutation. The chromosomes may change soon after crossing. The steady progress of the GA method is abruptly stopped. It is used to research solutions on a different website instead of seeking the most recent, best options.

… 10,001,000 …

↓ mutation …

00,010,001 ....

Because using complex genetic operators would make running the program more challenging, the suggested method avoids doing so.

(1) Start a group of people at random.
(2) Evaluate the original Solution using the fitness function.
(3) Go on as long as (1) is true
(a)Apply the elitist selection algorithm
(b) use person-point crossings
(c) use a specific mutation rate
(4) The number of individuals will be updated as more children are born.
(5) Conclude
(6) Form the cluster around the chromosome that fits the best.
GAECH is the first algorithm.

4. Experimentation and Results. The suggested installation approach has been implemented on a machine with a Core (TM) i5, 2.7 MHZ, 16 GRAM, and the latest version of Windows as the platform to demonstrate its viability and efficiency. As already stated, the target region is conceptualized as M N grid points. According to established principles, energy equilibrium and regulated boundaries collect various forms of data and create numerous bunch structures [10]. Its main objective is to significantly increase the processing, storage, and power of sensor layer hubs. I'm in charge of gathering the useful material for the sensor layer. Extension: Since each sensor layer corner covers multiple interest hubs, the ground unit receives information related to the intersection of interest features in a box. It is quite well-structured. Alternatively, you will see a list of several tasks between a specific objective hub and numerous monitoring centres. When the organization is prepared, these arrangements are appropriate. Despite this, there were better sites for the continued structure due to changes in network activity and the environment than this initial beginning strategy. Every hub in the organization has its power RPu set to 3 mW. This is 8 40t 2.0 10 regarding the functional relationship between communication power and sends distance [12]. A maximum communication intensity of 250 million watts and a maximum transmission distance of 20 m are both configured for the hub. Every seat in organization sends packages at four bundles per second once reproduction has started. The working principle of GA is shown in Figure 4.1.

Target hubs are arbitrarily selected from the group until the reenactment is through. Set the information transmission rate 6R = 10 pieces/sec and the size of the information bundle sent from the hub to L = 512 bytes and 512 bytes, respectively. As a result, the energy used by the transmitting hub u and the receiving hub v for each information packet delivered is P (u) * L/R and *RPvLR. The ND parcel's transmission time in the recreation is 4 seconds. The hub values for a 7-hub heterogeneous remote sensor organization. Every organization hub for the heterogeneous organizations transmits information with the highest possible communication power, independent of geography. The organization hub consumes power very quickly, and the power hub's excess energy is less than 100mJ. A few seats in the company are also rashly consuming a lot of force due to the unevenness in hub power use [6]. Nevertheless, this represents the cost incurred to modify the hub's energy usage, which lengthens the organization's existence.

4.1. Fitness performance. The fitness of biological inheritance, a measure of a person's survival and reproductive potential, determines their capacity [2] to pass on their DNA to others in a particular group. The genetic algorithm is used to evaluate each group member according to fitness. There is a purpose to wellness. The output from the input person can be the worth fitness has for the person in question.

4.2. Genetic programming. Genetic Programming (GP) is an evolutionary algorithm used to automatically develop computer programs to solve specific problems. Similar to genetic algorithms, genetic programming seeks solutions to problems by simulating the process of biological evolution, but its goal is to generate computer programs, not just optimize parameters. The biological evolution of animals is a lengthy and complex process that involves incremental optimization as lower species gradually develop into higher ones. The driving element behind the process is natural selection. Optimization techniques include copies, hybridizations, mutations, selection, and other operations. Academics have devised genetic algorithms (GA), which are based on the principles of biological evolution. The evolving algorithm offers a unique method of overcoming difficulties in search [9]. A genetic algorithm is made comprised of the three basic genetic operators of crossover mutation, selection, and inheritance.

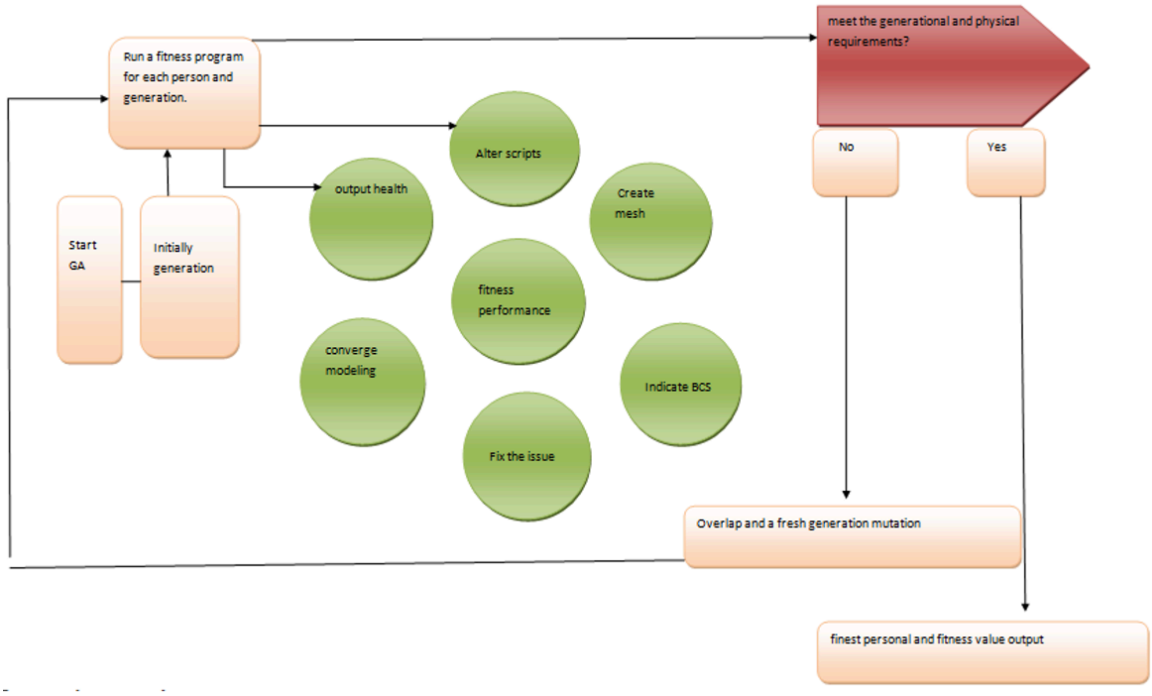

Fig. 4.1: Working of GA

4.3. Genetic algorithm mathematical model for best solution. By choosing people or genomes in the shape of Formula from an interval, we will apply the computational method suggested by Michalewicz [12] to get the biggest value of Eq. (4.1).

$$b_1, b_2, \cdots, b_{n_2} = (\sum n(i=0)b_{2i}) = X_i \tag{4.1}$$

There will be $A = 80$ chromosomes in this case, and every b-5 one will stand for an amino acid on one of them. Next, we convert x' into a number between 0 and 1, as shown in Eq. (4.2).

$$X_1 = L_{iow} + x_1 \frac{L_{up}}{2N-1} \tag{4.2}$$

Chromosome with the best performance is 0110111100001110101010011000110011.
(3) Equation (4)'s best chromosomal codifies the answers to the previous equations. (2) and (3) as
$x = 0.40452235290145597$ and
$y = 2.072061602212456$ for performance or fitness.

4.4. Schematic of a genetic algorithm. The crucial steps for the solution are as follows: Before turning the study's parameters into chromosomal code chains, identify the coding scheme used; the answer to each problem correlates to a signal string. 2) Initialization: Create a randomly chosen initial group with a population dimension P and a list of resolvable optimization problems. 3) The measure of fitness has been created, and the predicted fitness level for each person in the population is available. 4) Choose the action: The number of times an individual regenerates are determined by the fitness function chosen, and the optimized person is then included to the following cohort. Add new spouses or generations that have migrated to the following era. 5) cross: The preceding generation of the process is changed by removing two randomly chosen individuals from its organizational structure or content exchanger component. 6) Variation: The random chromosomal genes in the population are altered. Following selection, cross, and mutation procedures, group P will transform into a new

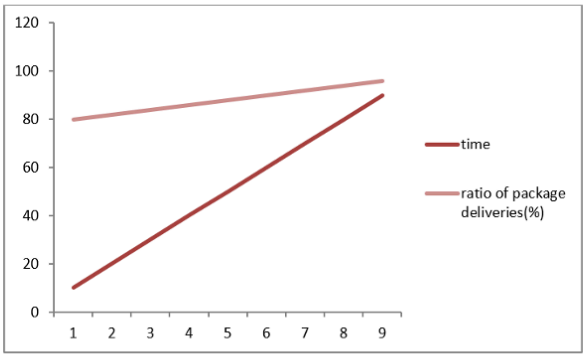

Fig. 4.2: Time taken for packet delivery within sensor node

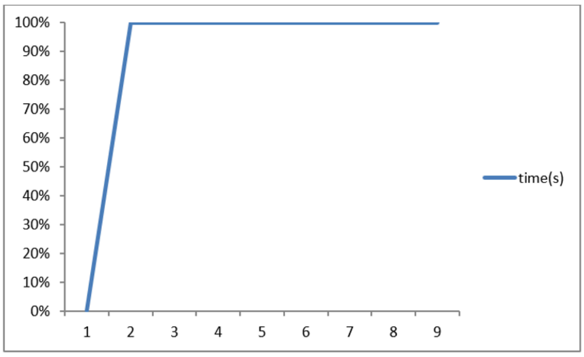

Fig. 4.3: Simulation outcomes of sensor nodes

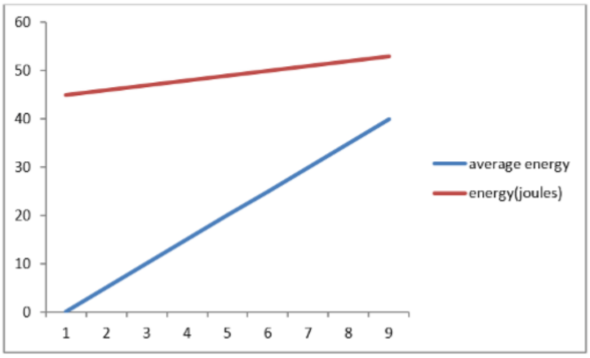

Fig. 4.4: Determining average energy of nodes as per GA

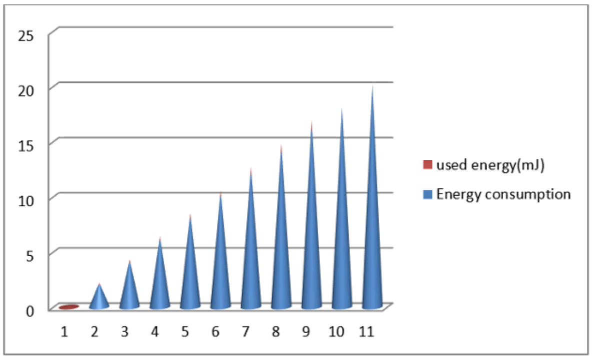

Fig. 4.5: Overall energy used by sensor node

group P based on a predefined probability of mutation Pm.17) Reiterate: If the best solution is identified, the process should be finished. If not, repeat step 3 to reassess, pick, combine, and manage the following groupings. This procedure is carried out again until the best fitness provider is found.

4.5. A crossover with sensor nodes. Selecting the optimum cross-operation phases to get to the fastest solution can speed up genetic processes. A new route is required since crossing in a genetic algorithm cannot change the initial good cluster path. Assume that accessing two current pathways from A to B is possible. The new path, which incorporates the benefits of the two ways, has been optimised in comparison to the two approaches employed in the previous generation because it is the common junction of the two paths mentioned above [6]. As shown in Figure 4.2, Figure 4.3.

4.6. A change of genetic algorithm with sensor nodes and packet transfer. A few gene loci on each specific chromosome sequence are altered as the main objective of the mutation operation. The strategy of the study, which also incorporates the substitution procedure, facilitates the cross-over operation. The final answer will be quite close to the ideal as a result, and a new information path called Ak2k4k5ki... B will appear. On this information path, the main operations will involve bridge auxiliary work and cross operation. If the chromosomes are modified to form a cluster k4, these changes will occur in k4 and have a corresponding impact on k6. In addition, it is expected that the mobile phone sink will use rechargeable technology, and it is unlikely to malfunction during testing. These detailed plans and operations will help ensure the smooth achievement of goals. As shown in Figure 4.4 and Figure 4.5.

5. Conclusion. In the article, a unique approach based on the Genetic Algorithm was developed to maximize area coverage. Using fewer randomly distributed data gathering nodes, this technique was created to increase the network's coverage. When selecting the initial population, it is critical to consider the diversity of the groupings, the calibre of the participants, and the likelihood that each group would succeed. In particular, competitiveness and genetic algorithms investigate these issues. It also shows that it is more dependable and stable than alternative methods. The simulation results evaluated the effectiveness of the suggested paradigm in terms of improved coverage and reduced network expenses. However, further work will be required to put the suggested strategy using a probabilistic detection model into practice.

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