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# *ENERGY EFFICIENT NANO WEARABLE DEVICES OPTIMISED WITH INTEGRATION OF GAINING SHARING KNOWLEDGE ALGORITHM FOR REAL-TIME HEALTH MONITORING*

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**ABSTRACT**

Nano-wearable healthcare devices that capture physiological data precisely and continuously for real-time health monitoring. However, maintaining continuous and efficient functioning is difficult on finite energy sources, including energy harvesters. A task scheduling technique working on the Sharing Knowledge (TS-GSK) methodology is presented in the present research to maximise energy consumption in nano-wearable health monitoring devices. The system dynamically distributes computer resources to activities carried out by nanoscale temperature and heart rate sensors, reducing duplicated operations and increasing power efficiency. This research for-lab nano-wearable device's data validates the suggested architecture, significant gains in sensor performance, job completion delays, energy efficiency, and dependability. Furthermore, GSK-based scheduling outperforms existing methods to efficiently handle resource constraints without compromising overall responsiveness. This task scheduling system ensures nano-wearable healthcare devices' operation and dependability by offering a workable and effective solution to energy issues.

*Keywords:* Nano-wearable devices, Gaining–Sharing Knowledge (GSK), Task Scheduling, Energy Optimization, Real-time Health Monitoring.

## 1. Introduction

### *a. Nano-Wearable Devices in HealthCare*

The development of nano-wearable medical devices has wholly transformed the healthcare industry by enabling the ability to monitor physiological parameters like heart rate and temperature constantly. [1]. Such devices, characterised by their reliability and small size, offer continuous information that can improve remote patient monitoring, fitness, illness management, and care for seniors. However, ensuring effective and long-lasting functioning is a significant issue, especially given their dependency on resource-harvesting machines. Although they enable battery-free functioning, these energy sources frequently generate irregular power, endangering the device's efficiency [2].

Traditional task scheduling methods cannot handle the unpredictable characteristics of nano-wearable systems due to the constant flow of data through nanoscale sensors, which is



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required for computing employment opportunities [3]. This results in duplicated procedures, inefficient energy use, and unstable system performance. As a result, task scheduling is required to minimise wasteful energy use and dynamically compute resources [4].

*b. TS-GSK in Health Monitoring*

A task scheduling method that depends on the Gaining-sharing Knowledge (GSK) techniques has been proposed in the present research. Motivated by human interaction, GSK gives a reliable and flexible solution for challenging optimisation issues [5]. According to research results from a prototype system, the defined technique uses GSK to reduce redundant jobs, improve power consumption, and guarantee dependable operation in nano-wearable devices.

The description of this study can be explained as follows:

- ✓ An innovative scheduling methodology works on GSK and is developed for the first time to evaluate energy utilisation and ensure the lowest energy consumption in nano-wearable medical equipment[6].
- ✓ Comparative optimisation outperformed the latest generation of flower pollination algorithms (FPA) in terms of both task reliability and energy consumption.
- ✓ The impact of enhanced task scheduling on device lifetime and reliability was meticulously investigated, demonstrating notable enhancements in battery lifespan and system responsiveness.

The rest of this research is organised as follows: Section 2 provides a comprehensive literature review on wearable medical devices, energy harvesting technologies, and task scheduling algorithms. Section 3 describes the system architecture and data profiling process. Section 4 elaborates on the problem formulation and the GSK optimisation algorithm. Section 5 presents experimental results and a comparative performance analysis. Lastly, Section 6 concludes the study and future research directions.

## 2. Literature survey

Samah Mohamed et al.[7] wearable medical devices, namely those with temperature and heart rate sensors, the research presents a task scheduling relying upon the GSK algorithm that optimises energy usage. The experimental findings demonstrate significant energy savings, increased task dependability, and longer gadget lifetime. Some drawbacks include reliance on lab-based prototypes, sensor scaling problems, and unpredictability of energy harvesting.

D. Verma et al.[8] The potential for real-time illness diagnosis, monitoring, and treatment is highlighted in the present article, which examines the role of 5G technology and wearable IoT devices in healthcare. The value of wearable technology is increased by incorporating 5G, which permits quicker, low-latency data transfer. Challenges have been covered, including power constraints, privacy issues, and system integration. These obstacles enhance IoT-based healthcare solutions; this research highlights the necessity for further investigation.

Z. Deng et al.[9] The developments in innovative wearable health monitoring systems are covered in this research, with particular attention paid to biosignal evaluation, integration of systems, and choice of material. It demonstrates innovations in wearable technology that may monitor fitness continuously and are portable and versatile. The research paper discusses difficulties, such as balancing system resilience, sensing performance, and adaptability.

Challenges include enhancing the device's functionality, comfort, and lifetime for detecting and treating diseases.

D. Xie et al.[10] deep learning-based algorithms for gait phase recognition, the research introduces the wearable energy-efficient fitness tracking (WE2FT) structure, which tracks athletes' health. Using the CM3A route loss model, the system optimises communication and energy efficiency while integrating an application for smartphones and Internet of Things technologies for real-time step monitoring. According to simulation data, the system performs well regarding route loss and energy efficiency. The requirement for additional optimisation in practical applications and possible difficulties in the scalability of the system for various user situations are among the limitations.

J. V. Vaghasiya et al.[11] The developments in wearable technology for telehealth are covered in this study, with an emphasis on 2D materials-based sensors for monitoring health remotely. It discusses the principles, capacities, and uses of five different types of sensors: temperature, pressure, strain, electrochemical, and optoelectronic. The research paper addresses the difficulties and prospects for enhancing these wearable sensors' functionality and performance. Some limitations are demands for more advancements in sensor integration, robustness, and scalability for broad use.

S. Shajari et al.[12] materials, structural designs, and transduction processes for physical, chemical, and biosensors, the present work examines developments in wearable sensors with AI capabilities for health monitoring. It emphasises using AI in real-time data collection, massive data processing, and customised healthcare. The results show increased sensor efficiency, accuracy, and capacity for illness diagnosis. The limitations are reliability, scalability, and smooth interaction with current healthcare systems.

Ethan Zhu et al.[13] Through the dynamic distribution of processing jobs among devices and mobile applications, the study suggests an active computation offloading technique to minimise the power consumption of health monitoring devices. The collection contains data from wearable sensors used for real-time health monitoring. The outcomes are improved scalability, cost-effectiveness, and a 20% decrease in system power usage. Limitations include reliance on mobile computing power, device compatibility, and possible data offloading delay.

## 3. System Description

### *a. System Overview*

The proposed methodology optimises energy use in nano-wearable health monitoring devices using the Gaining–Sharing Knowledge (TS-GSK) algorithm. It ensures effective job scheduling and redundancy by dynamically allocating and evaluating resources to nanotechnology sensors, such as heart rate and temperature monitors. The architecture must be highly responsive and reliable while addressing energy restrictions. Validation is based on nano-wearable device data, which shows increased sensor performance, decreased job delays, and improved energy economy. The system outperforms current approaches regarding energy economy and overall functionality, guaranteeing consistent, reliable operation through efficient resource management.


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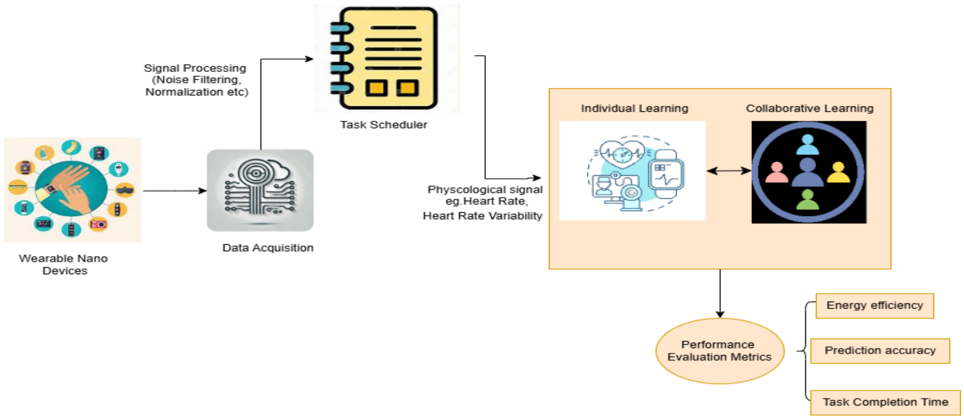


**Figure 1:** TS-GSK Algorithm for Health Monitoring

### b. *Data Acquisition*

The pre-processing module gathers and prepares for analysis, which is crucial to health monitoring systems. This component carries out several essential tasks, such as collecting data from a variety of devices and user inputs, containing demographic data (e.g., age, gender), day-to-day routine characteristics (e.g., sleep length, alcohol intake), and physiological measures (e.g., heart rate, blood oxygen level). The quality of the data and the procedure eliminate outliers, fix mistakes, and handle missing numbers. It also standardises data to a consistent scale without distorting variations in the ranges of values.

*Pre-processed Data Representation:* Let $D_i(t)$ defined the raw data from sensor $i$ at time $t$. The pre-processed data$P_i(t)$ can be described in the following equation 1:

$$P_i(t) = f\big(D_i(t)\big) + \epsilon(t) \qquad (1)$$

Where $f\big(D_i(t)\big)$ Defined as a Signal processing function (e.g., noise filtering, normalisation), $\epsilon(t)$ is represented by Error correction or imputation for missing or corrupted data. If compression is applied, let the compression ratio be the compressed pre-processed data.$P'_i(t)$ is:

$$P'_i(t) = \frac{P_i(t)}{C}, \qquad C > 1 \qquad (2)$$

Data reduction in health surveillance systems minimises the amount of pre-processed sensor data, saving storage space and transmission energy. The compressed information equation (2) can be extracted by using a compression factor of $C$ $(where\ C > 1)$to process information. $P_i(t)$ From device $i$ at time $t$. Since it increases battery life and improves data transmission efficiency, this procedure is essential for wearable technology. For instance, with a typical compression ratio of 2.25x, system-on-chip (SoC) with on-chip lossless data compression considerably reduces data size without sacrificing signal quality.

### c. *Task Scheduling and Optimisation*

Health monitoring systems' task scheduling and optimising components use Gaining-Sharing Knowledge (GSK) to manage resources by dynamically allocating computing activities to maximise energy usage. The Feature Selection Methodology finds the most pertinent data characteristics, such as physiological measures, to enhance predicted quality. The device's performance and dependability and the system's ability to balance calculation needs with resource limitations by combining these modules guarantee precise health monitoring and efficient energy consumption.

To minimise total energy consumption $E_{total}$while executing a set of tasks $\{T_J\}$ on available computational resources $\{R_k\}$, the following optimisation problem can be formulated:

Minimise

$$E_{total} = \sum_{j=1}^{n} E_j T_j \tag{3}$$

Subject to

$$\sum_{k=1}^{m} R_k \, T_j \leq R_{max} \ ,\forall j \tag{4}$$

$$E_j T_j \leq E_{avail}, \forall j \tag{5}$$

Where $E_j T_j$ Does the task consume energy? $T_j, R_K T_j$represents the computational resources allocated to the task $T_j$, $\boldsymbol{R_{max}}$ Denotes the maximum available resource capacity of the resource management. $E_{avail}$ The available energy. Feature selection is essential for improving prediction accuracy and lowering the computing burden in nano-wearable systems. Extract beneficial characteristics to track cardiovascular health by concentrating on signals like heart rate (HR), heart rate variability (HRV), and electrocardiogram (ECG) data.

### *d. Energy Management Using Gain-Sharing Knowledge*

A health monitoring technique's energy production and expenditure may be tracked and optimised with the help of Resource Management. It assures that the energy obtained from various sources, such as bodily motions or environmental conditions, is effectively employed to drive the system's functions. In mathematical terms, the net available energy at any given time $t$, represented as $E_a(t)$, is computed by subtracting the integrated consumed energy $E_c(t)$over time from the harvested energy $E_h(t)$:

$$E_a(t) = \int_0^t E_h(\tau)d\tau - \int_0^t E_c(\tau)d\tau \tag{6}$$

The energy harvested at time $t$, $E_h(t)$can be modelled as the product of the harvester's efficiency $\eta$ and the power generated $P_{harvest}(t)$:

$$E_h(t) = \eta . P_{harvest}(t) \tag{7}$$

The Energy Management Module may use the information to anticipate and optimise energy use, including heart rate, sleep length, and activity levels. For example, the monitoring device may use more energy when heart rates or physical activity are higher because of increased data processing and transmission demands. The module may use dynamic task scheduling for the dataset's patterns to maintain system efficiency and dependability by ensuring energy consumption. $E_c(t)$ never exceeds available energy $E_a(t)$ At any given time $t$.

The gaining–sharing information (GSK) algorithm is an optimisation technique inspired by nature that mimics how people socially acquire and share information at various stages of life. The initial and final stages are the two main operating phases. Individuals (solutions) in the initial stage pick up information from their close social circles, including families and relatives, and disseminate it within their network. As learners reach the final stage, they exchange ideas and broaden their learning to include professional colleagues and social media.



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**Table 1:** TS-GSK Algorithm for Health Monitoring

**Step 1:** Randomly generate a population of potential solutions within specified constraints. Each individual $x_i$ is initialised as

$$x_i = LB + rand * (UB - LB) \tag{8}$$

Where $LB$ and $UB$ are the decision variables, and $rand$ is a random number between 0 and 1.

**Step 2:** Allocate junior and senior phase dimensions based on progression and a knowledge rate. Calculate the number of dimensions assigned to the Junior and Senior phases for each individual based on the current generation $G$, maximum generations. $G_{max}$Total dimensions $D$, and a knowledge rate parameter $K$:

$$D_J = D * (1 - \frac{G}{G_{max}})^k \tag{9}$$

$$D_s = D - D_J \tag{10}$$

Where $D_J$ and $D_s$ What are the dimensions for the Junio and Senior phases.

**Step 3:**Update individuals by learning from better and worse neighbours and sharing with a random peer at the initial phase. Update the individual's position.

**Step 4:**Refine solutions by interaction with the population's best, middle, and worst representatives at the final phase.

**Step 5:** Revaluate fitness and repeat until convergence or maximum generations

## 4. Result Analysis

### *A. Energy Efficiency*

**Table 2: Comparison Table for Energy Efficiency**

| Time Slot | GSK Energy Efficiency % | FPA Energy Efficiency% |
|---|---|---|
| 1 | 85 | 78 |
| 2 | 88 | 82 |
| 3 | 90 | 80 |
| 4 | 92 | 84 |
| 5 | 93 | 85 |
| 6 | 95 | 87 |
| 7 | 96 | 88 |
| 8 | 97 | 89 |

The improved energy optimisation capabilities of GSK over FPA are demonstrated by empirical data from an in-lab nano-wearable prototype that integrates nanoscale temperature and heart rate sensors. For energy redundancy and to maintain operational dependability across a range of periods, the GSK algorithm dynamically distributes computing resources. These findings demonstrate how resilient GSK is to significant energy limitations in real-time nano-wearable health monitoring systems.

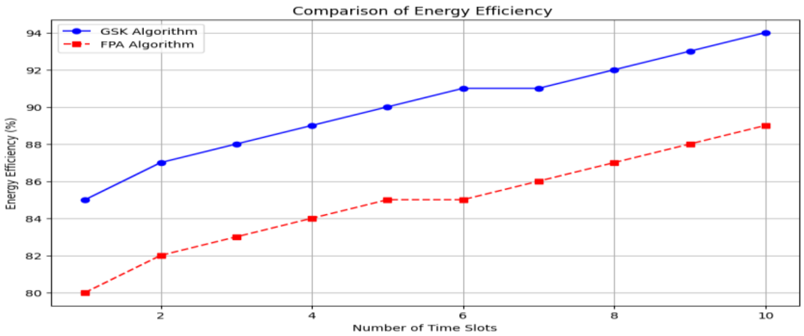


**Figure 3:** Comparison of Energy efficiency

The graph contrasts the energy efficiency of the Flower Pollination Algorithm (FPA) with the Gaining-Sharing Knowledge (GSK) algorithm for nano-wearable medical devices over various time windows. While energy efficiency (%) is displayed on the y-axis, the x-axis indicates the number of time slots. The evaluation used data from an in-lab nano-wearable prototype equipped with temperature and heart rate sensors at the nanoscale. According to the results, GSK continuously performs better than FPA, showing less computational redundancy and an excellent energy economy. Demonstrates how well GSK optimises power use and guarantees dependable gadget functioning.

### *B. Prediction accuracy*

**Table 3:** Comparison Table for **Prediction Accuracy**

| Time Slot | GSK **Prediction accuracy** | FPA **Prediction accuracy** |
|---|---|---|
| 1 | 88 | 80 |
| 2 | 90 | 82 |
| 3 | 92 | 83 |
| 4 | 93 | 84 |
| 5 | 94 | 86 |
| 6 | 96 | 87 |
| 7 | 97 | 88 |
| 8 | 98 | 89 |

Through the graphic representation of accuracy values for both methods over time windows, the table supports the graphical analysis. While FPA demonstrates a slower performance growth rate, GSK consistently improves accuracy, demonstrating GSK's efficiency.

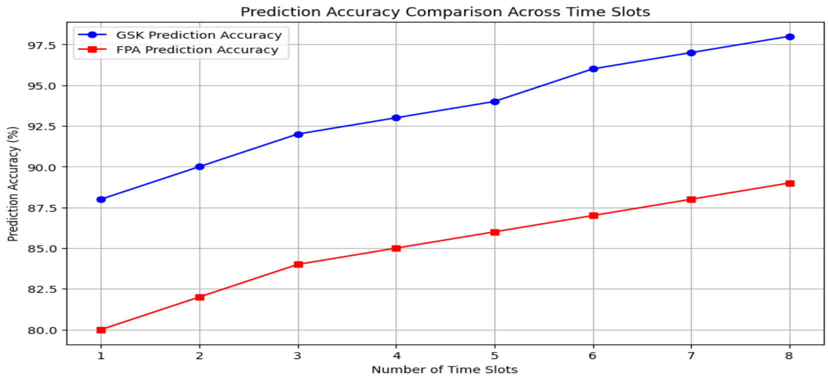


**Figure 4:** Comparison of Prediction accuracy

The prediction accuracy score of the GSK and FPA algorithms across several time slots is depicted in the comparison graph. GSK's effective resource allocation and work scheduling methods enable it to constantly exceed FPA, exhibiting greater accuracy values at every interval. The graph shows that GSK's accuracy steadily increases, whilst FPA shows comparatively slower growth. This discrepancy in performance demonstrates how well GSK optimises job execution and energy efficiency in nano-wearable technology.

### *C. Time Completion Task*

**Table 4:** Comparison Table for Task Completion Time

| Dataset Size | GSK **Task Completion Time** | FPA **Task Completion Time** |
|---|---|---|
| 1 | 8.2 | 9.5 |
| 2 | 7.5 | 9.0 |
| 3 | 7.0 | 8.8 |
| 4 | 6.8 | 8.6 |
| 5 | 6.5 | 8.4 |

Task completion for GSK and FPA in five different situations are displayed in the table, with GSK continuously obtaining minimum timings. Both approaches show improvement as the situation continues, although GSK is more efficient than FPA. It finally shows how well-suited GSK is to managing increasingly complicated activities or more enormous datasets.

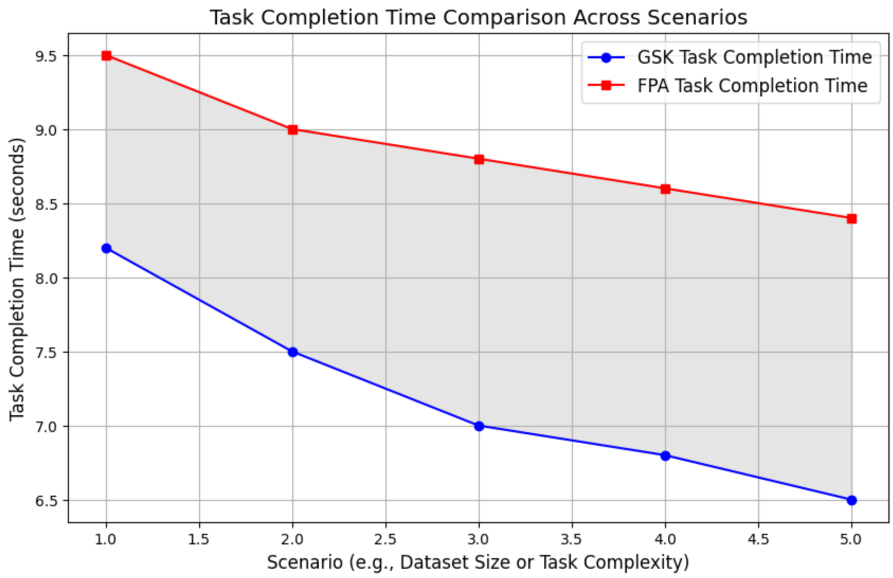


**Figure 5:** Comparison of Task Completion Time

The task completion time graph shows the job completion times for two methods, FPA and GSK, under various conditions (e.g., problem difficulties or dataset sizes). Quicker task completion times across circumstances show that GSK routinely performs better than FPA. FPA less dramatically, going from 9.5 seconds to 8.4 seconds, while GSK's time drops from 8.2 seconds to 6.5 seconds. The darker area, representing the performance disparity, emphasises GSK's efficiency advantage. This investigation shows how effective and scalable GSK is, which makes it a superior choice for applications that need to handle larger datasets or more complicated tasks quickly.

## 5. Conclusion

The nano wearable medical devices are crucial for ongoing health monitoring, yet battery issues frequently constrain them. An environmentally way to guarantee continuous functioning is through energy harvesting. The present research employs job scheduling to optimise sensor performance in such devices. We looked at a situation with the temperature and cardiovascular sensors. The task scheduling Gaining Sharing Knowledge (TS-GSK) methodology was used to reduce power usage and increase energy efficiency. According to the results, GSK performs noticeably better than the Flower Pollination Algorithm (FPA), providing the fastest calculation and better energy management. It has been shown that GSK successfully schedules energy-efficient tasks for wearable systems. Future research should investigate incorporating more sensors, sophisticated optimisation approaches, and enhanced energy harvesting systems for more sustainable gadget performance.

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