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Multi-Objective Optimisation for Reliability Improvement in Biosensor-based Cyber-Physical Systems

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Abstract - Integrating biosensors into Cyber-Physical Systems (CPS) enables the development of advanced real-time healthcare solutions, including remote monitoring, diagnosis, and treatment. The incorporation of advanced biosensors into healthcare CPS systems, however, raises concerns about sensor consistency and reliability amid environmental uncertainty, data noise, and the complexity of these systems. This study proposes the first known multi-objective optimisation approach to improving the reliability of biosensors in CPS while accounting for performance and resource constraints. This approach will improve reliability as a multi-objective problem, where simultaneous optimization of specific parameters, such as sensor accuracy, fault tolerance, energy/efficiency, and data transmission, will be accomplished. Next-generation systems will employ a variety of advanced optimisation methods (evolutionary methods, Pareto methods) in order to optimise conflicting goals. A sophisticated reliability model will be constructed to enable the optimal configuration of operational strategies and to account for real-time failures/uncertainties in biosensors. To demonstrate the validity of the proposed framework, simulations will be conducted on a CPS system using real biosensors. Compared with existing methods, the proposed model will demonstrate improvements in system reliability and operational effectiveness while maintaining adaptability to changing healthcare systems. The reliable CPS with biosensors framework will be the first of its kind to offer unprecedented intelligence with true system resiliency. The research results provide a basis for anticipating the next steps to be taken regarding the further integration of artificial intelligence and edge computing, with a focus on reliability in CPS architecture.

Keywords: Cyber-Physical Systems (CPS); Biosensors; Multi-Objective Optimization Evolutionary Algorithms; Data-Driven Modeling

1. INTRODUCTION

Cyber-Physical Systems (CPS) are a new approach to integrating the digital and physical by merging computing and intelligence, communications, and physical processes to enable real-time monitoring and control of a system [1]. In the last few years, the convergence of CPS with biosensor technology has created new opportunities for the development of smart healthcare systems [2-3]. These systems can monitor a user's physiology at all times, help detect diseases early, and assist in developing tailored treatment plans. Biosensors that can detect biological signals over a wide range and are of great importance at the interface between the digital and the physical in a CPS can improve the system's responsiveness and the quality of decision-making within the system [4].

Integrating biosensors with CPS introduces new challenges, such as reliability. The reliability of CPS with integrated biosensors is system-dependent due to sensor variability, noise, environmental factors, signal disruptions, communication delays, and other hardware and software failures [5]. In sensitive and critical healthcare scenarios, a system's unreliability can be very costly; therefore, developing methods to improve reliability while enhancing performance is of the utmost importance [6].

Most traditional approaches to improving reliability utilise either single-objective optimisation or incorporate heuristics, which tend to oversimplify the vexing complexities and conflicts that characterise the CPS environment. For example, improving a sensor's accuracy may, in fact, increase energy consumption, and increasing fault tolerance may increase the computational burden [7]. These complexities and conflicts require a multi-objective optimisation, in which the objectives are functionally integrated to achieve an optimally balanced system design.

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In this regard, multi-objective optimisation, especially when using evolutionary algorithms and Pareto optimality, is effective for addressing trade-offs in complex engineering design and optimisation problems [8]. These approaches illustrate possible optimal design trade-offs which provide system designers with choices regarding reliability, efficiency, and resource allocation. The use of these methodologies in biosensor-integrated CPS, particularly to improve reliability, remains a novel approach [9].

This proposal offers a multi-objective optimisation method to improve reliability in biosensor-integrated cyber-physical systems (CPS), focusing on system optimisation, fault tolerance, energy-based system optimisation, data transmission reliability, and sensor accuracy [10]. By using cutting-edge optimisation methods, this proposal aims to improve system reliability and allow for changing healthcare system environments.

This document makes the following contributions:

(i) Creates a reliability-focused multi-objective optimisation model for biosensor-integrated CPS,

(ii) Integrates the reliability model with device-based systems, real-time systems, and device parameters, and

(iii) Test-based system optimisation works better than traditional optimisation systems for CPS.

The rest of the paper is organised, with Section 2 outlining a review of the most relevant biosensor studies, CPS, and optimisation methods. Section 3 reveals the proposed methods. Section 4 provides empirical findings and analysis, and in Section 5, the author will conclude and provide specific points for future studies.

2. LITERATURE REVIEW

The last few years have seen a growing acceptance of Cyber-Physical Systems (CPS). They let engineers build systems that fuse computer-based intelligence with tangible, physical processes. There are many degrees of real-time sensing, monitoring, and control [11]. The biosensors integrated into CPS also enable intelligent healthcare systems that monitor and analyse physiological data, and make recommendations based on these data [12].

2.1 CPS and Reliability Problems

The cyber and physical parts of CPS are strongly interconnected, so each depends on the others to work reliably. This problem creates reliability issues, including communication lag, sensor malfunctions, cyber sabotage, and environmental uncertainty. Most recent studies indicate that achieving reliability in CPS requires a systems approach that treats both layers as parts of the same whole [13].

The leading models for CPS reliability have been categorised into three types: analytical, simulation, and hybrid. These types of models use fault trees, Markov models, and availability-based metrics to estimate system performance in the event of failure. CPS environments are dynamic and present a range of factors that challenge traditional reliability models. This is especially true for real-time data and distributed sensor systems[14].

In addition, the expanding scale and growing heterogeneity of CPS have magnified reliability concerns. An example is the growing importance of CPS reliability, which has warranted increased focus on anomaly detection and fault diagnosis [15]. Recent results obtained in adaptive anomaly detection show that most participants focus on one of the two data adaptation and model adaptation, and rarely both, which results in the system operating below expectations. This has demonstrated the need for a broader and more adaptive reliability framework [16].

2.2 Role of Biosensors in CPS

Biosensors are essential to CPS, acting as critical points of contact between computational systems and the real world. Innovations in biosensor technology, such as flexibility and MEMS (Micro-Electro-Mechanical Systems) technology, enable real-time

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monitoring of systems in both healthcare and environmental monitoring [17]. These systems can be created with a high degree of sensitivity, miniaturised to small formats, and produce large volumes of data that require monitoring and analysis [18].

Biosensors have been a focal point of research over the last few years, contributing to the enhancement of CPS in healthcare and enabling early diagnosis and personalised healthcare. Flexible biosensors are sensors used in systems that continuously monitor the wearer and provide highly accurate physiological information, regardless of the effort the wearer exerts (no matter how the wearer moves)[19]. On the same note, MEMS biosensors have proven to improve the precision and efficiency of real-time monitoring across a variety of fields, including healthcare and environmental monitoring. Despite the many benefits biosensors provide, they introduce several new reliability issues for CPS [20]. Sensor drift, calibration shifts, noise, and environmental factors will always introduce new complications and degrade the data, adversely affecting the systems. Additionally, adding multiple biosensors with varying types and functionalities increases the system's complexity. As a result, minimising system reliability needs to be undertaken.

2.3 Optimisation Techniques in CPS

Optimisation is fundamental to improving the CPS; in particular, it requires analysing trade-offs among competing goals, such as system reliability, energy consumption, and computational costs [21]. Optimisation is a primary method used in the CPS, and it may be traditional (deterministic and heuristic) or emerging. These optimisation methods, however, are less efficient for multi-dimensional, conflicting objectives. Empirical studies in recent years have focused on more sophisticated optimisation methods, such as evolutionary and stochastic optimisation, as well as hybrid methods. For example, a systematic analysis of optimisation methods in cyber-physical infrastructure shows a growing trend toward using both deterministic and stochastic models to address system disruption and improve resilience. These models comprise numerous decision variables, constraints, and objective functions. Such models are well-suited to the complexity of a CPS. The optimisation of sensor placement and system reliability is an example of an emerging optimisation problem, particularly within graph-based and diffusion models [29]. For example, optimising sensor placement in the CPS uses advanced algorithms and demonstrates that optimising both the physical and cyber layers of a system can improve communication and reliability. These models, therefore, illustrate the need to optimise the system design to improve the system.

2.4 Intelligent and Data-Driven Approaches for Reliability Improvement

The use of artificial intelligence (AI) and machine learning (ML) with cyber-physical systems (CPS) has created new ways to improve reliability. Improved reliability is achieved through predictive maintenance, and systems become more resilient through anomaly detection and adaptive control [30]. Federated learning, for example, has emerged as a promising technology for distributed operational CPS, given the importance of data privacy and limited communication. Adaptive federated learning has been shown, in some instances, to improve the accuracy of such learning frameworks while maintaining system reliability under node failures and resource constraints. In biosensor-based systems, where data is generated at a large number of distributed nodes, such learning frameworks are especially needed. In addition, the use of AI for improving the reliability and security of CPS has been widely investigated. Intelligent monitoring systems have been proven to detect cyber threats and system anomalies, thus increasing operational safety and reliability. These findings illustrate the need to combine AI with optimisation and reliability modelling in CPS [31].

2.5 Gaps in Existing Literature

Despite advancements made in related areas, the literature still has many gaps. First, most studies focus on CPS reliability, biosensor technology, or optimisation, and there is little literature that considers all three areas together. Second, many optimisation methods are single-objective and do not capture the trade-offs among the three components of reliability, energy efficiency, and system performance [32]. Furthermore, many reliability models do not account for the uncertainty and variability of real-time biosensor data, which is very important in healthcare. Although AI and machine learning have contributed in some way, their combination with multi-objective optimisation is the least studied area for the reliability of CPS with biosensors. Lastly, there are very few studies that integrate probabilistic reliability models, characteristics of biosensor data, and sophisticated multi-objective optimisation models within a single CPS framework. This undersells the potential of implementing an adaptive, robust, and scalable CPS across a variety of real-world cases [33].

The literature points to the growing relevance of cyber-physical systems (CPS) in today's applications and to the importance of biosensors for smart, adaptive monitoring systems. Although advancements have been made in reliability modelling, optimisation, and AI, there remains an evident lack of cross-sectional frameworks for the biosensor-based CPS trade-off. This study seeks to address this by developing a multi-objective optimisation framework to improve reliability in biosensor-integrated CPS [34].

2.6 Research Gap

An increasing number of studies address Cyber-Physical Systems (CPS) with biosensors and biosensor optimisation, but frameworks for the integrated reliability of these growing areas remain under development. Most studies focus on the reliability of CPS, the performance of biosensors, or the isolation of optimisation, which yields fragmented solutions and does not consider the relationships among sensor accuracy, system reliability, and operational efficiency. Additionally, baseline studies focus on single-objective optimisation techniques that are ineffective at balancing the conflicting demands of reliability, energy consumption, fault tolerance, and data-carrying throughput of a biosensor-embedded CPS. In the last few years, while systems have been adapted and improved using the principles of Artificial Intelligence and data-driven systems, very few have been developed with multi-objective optimisation principles, focusing on increased reliability [35]. Also, reliability frameworks often oversimplify or ignore the stochastic behaviour of biosensor data due to noise, drift, and varying environments. For extensive optimisation addressing CPS-confidential areas such as healthcare, it is vital to address this significant deficiency in CPS configurations: multi-objective optimisation, real-time uncertainty in biosensors, and systems-level performance metrics.

*2.7 Novelty and Contributions *

The unique value of this research lies in providing the first comprehensive multi-objective optimisation framework for addressing CPS reliability challenges with biosensors. Previous work has focused on pliable, piecemeal approaches to CPS. In contrast to standard approaches that view the reliability, energy, and performance of a system in isolation, our framework interlinks and harnesses the value of these competing factors, differentiating our optimisation approach from others. A distinguishing aspect of this research is that it is the first to synergise the framework with probabilistic reliability modelling and the real-time characteristics of biosensors to capture parameter, measurement, and intelligence drift, along with sensor environmental variation.

A further development of this research will include state-of-the-art evolutionary and Pareto-based multi-objective optimisation approaches to model the trade-offs among the system's conflicting requirements, generating a set of undominated solutions and easing the decision-making process across different use-case scenarios [36]. Also of additional significance is the inclusion of an often neglected performance framework for optimising CPS, namely reliability-aware performance metrics such as fault tolerance, data reliability, and communication efficiency. In addition, the proposed model aims to be scalable and adaptable for use in dynamic, distributed CPS environments and intelligent healthcare systems. The framework is validated through simulations and compared with the conventional single-objective and heuristic methods. The framework has been shown to have better reliability and operational efficiency [37].

The major contributions of this research work are:

(i) a new, combinatorial multi-objective optimisation framework for increasing reliability in biosensor-integrated CPS;

(ii) the first integration of a model of reliability presented in a probabilistic form with the uncertainty of the biosensor in real time;

(iii) the first application of such sophisticated Pareto-based optimisation approaches to conflicting objectives; and

(iv) evidence of great performance and high reliability of the proposed method, in a CPS-based healthcare monitoring system, obtained in reality.

3.0 METHODOLOGY

This part explains the multi-objective optimisation framework designed to increase the reliability of biosensor-integrated Cyber-Physical Systems (CPS) [38]. The method combines three aspects: probabilistic reliability modelling, uncertainty in biosensor data, and Pareto optimisation, and fuses them in one system. The whole framework is divided into four major parts: (i) system modelling, (ii) reliability formulation, (iii) multi-objective optimisation, and (iv) solution evaluation[38].

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3.1 System Architecture of Biosensor-Integrated CPS

The suggested CPS system architecture comprises three major parts.

(i) Physical Layer (biosensors and environment),

(ii) Cyber Layer (data processing, communication, and control),

(iii) Decision Layer (optimisation and reliability evaluation).

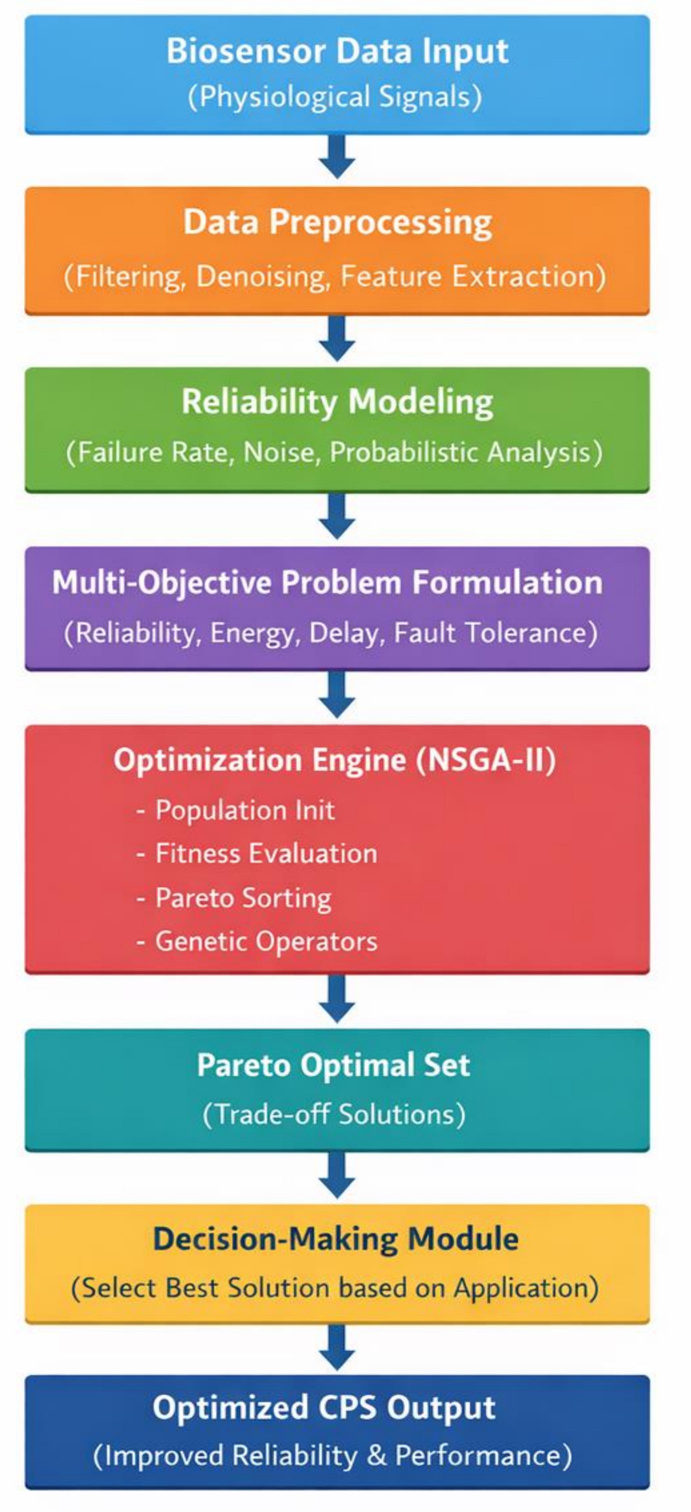

Figure 1 Proposed Methodology in the Optimisation of CPS

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The biosensors in the physical layer gather physiological data (e.g., heart rate, temperature, biochemical signals) and pass that data to the cyber layer. In this layer, data is preprocessed and filtered, and relevant features are extracted. After that, the decision layer assesses system reliability and uses optimisation to adjust the performance[39].

3.2 Reliability Modeling

The biosensor-integrated CPS is considered reliable if the system accurately executes its function and achieves its purpose within a given time and under a defined set of parameters. The reliability of a system is probabilistic, given random biosensor data [40].

The reliability of the overall system is expressed as:

$$R_{\text{sys}} = \prod_{i=1}^{N} R_i$$

where R_i represents the reliability of the i^{th} component (sensor, communication node, or processing unit), and N is the total number of components.

Each sensor's reliability is influenced by noise, drift, and environmental factors, modelled as:

$$R_i = e^{-\lambda_i t}$$

where λ_i is the failure rate of the i^{th} sensor and t is the operational time. To incorporate biosensor uncertainty, a noise factor η_i is introduced:

$$R_i' = R_i(1 - \eta_i)$$

where $\eta_i \in [0,1]$ represents the degradation due to noise and signal variability.

3.3 Multi-Objective Optimisation Formulation

The reliability improvement problem is formulated as a multi-objective optimisation problem (MOP), in which multiple conflicting objectives are optimised simultaneously [41].

The general formulation is:

$$\text{Minimize / Maximize } F(x) = \{f_1(x), f_2(x), f_3(x), f_4(x)\}$$

where x represents decision variables such as sensor configuration, transmission rate, and processing parameters.

The objectives are defined as follows:

Objective 1: Maximize System Reliability

$$f_1(x) = \max R_{sys}$$

Objective 2: Minimize Energy Consumption

$$f_2(x) = \min \sum_{i=1}^{N} E_i$$

where E_i is the energy consumption of the i^{th} sensor node.

Objective 3: Minimise Communication Delay

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$$f_3(x) = \min \sum_{i=1}^{N} D_i$$

where D_i represents data transmission delay.

Objective 4: Maximize Fault Tolerance

$$f_4(x) = \max FT$$

Fault tolerance is defined based on redundancy and system recovery capability.

3.4 Constraints

The optimisation problem is subject to the following constraints:

- Energy constraint:

$$E_i \leq E_{\max}$$

- Delay constraint:

$$D_i \leq D_{\text{threshold}}$$

- Reliability constraint:

$$R_{\text{sys}} \geq R_{\min}$$

- Sensor capacity constraint:

$$C_i \leq C_{\max}$$

These constraints ensure that the system operates within acceptable performance limits.

3.5 Optimisation Algorithm

To address the multi-objective problem, the research utilises Pareto-based evolutionary methodologies, specifically the Non-dominated Sorting Genetic Algorithm II (NSGA-II).

The steps for the algorithm are as follows:

1. Establish a population for candidate solutions.

2. Analyse the objective functions for every solution.

3. Conduct a non-dominated sort for the identification of Pareto fronts.

4. Use selection, crossover, and mutation operators.

5. Produce a new set of offspring solutions.

6. Continue the process until the convergence criteria are satisfied.

The result of this process is a collection of Pareto-optimal solutions that reflect trade-offs among reliability, energy efficiency, and performance [42].

3.6 Flow Diagram of the Proposed Framework

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The complete workflow of the proposed methodology is as follows:

1. Input Stage

   - Data capture for the biosensor
   - Initialisation of system parameters

2. Preprocessing Stage

   - Noise suppression
   - Extraction of features

3. Reliability Modelling Stage

   - Estimation of failure rates
   - Computation of probabilistic reliability

4. Optimisation Stage

   - Definition of objective functions and constraints
   - Execution of the NSGA-II algorithm

5. Evaluation Stage

   - Generation of the Pareto front
   - Optimal solution selection

6. Output Stage

   - Configuration of CPS is optimised
   - Metrics of reliability are enhanced

3.7 Performance Evaluation Metrics

To validate the effectiveness of the proposed framework, the following metrics are used:

- Reliability Improvement Ratio (RIR)

$$\mathrm{RIR} = \frac{R_{\mathrm{opt}} - R_{\mathrm{base}}}{R_{\mathrm{base}}}$$

- Energy Efficiency
- Latency Reduction
- Fault Recovery Rate

These metrics provide a comprehensive evaluation of system performance.

Input:

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Population size (N)
Number of generations (G)
Objective functions (f1, f2, f3, f4)
Constraints

Output:

Pareto optimal solution set

Step 1: Initialize population Pe with N random solutions

Step 2: Evaluate objective functions for each solution

Step 3: Perform non-dominated sorting
→ Assign rank (Pareto fronts)

Step 4: Calculate crowding distance for diversity

Step 5: Repeat for generation $t = 1$ to G :

a. Selection:

- Use tournament selection based on rank & crowding distance
  b. Crossover:
- Generate offspring using crossover probability

c. Mutation:

Apply mutation to maintain diversity.
d. Create offspring population Qt
e. Combine populations:
$Rt = Pt \cup Qt$
f. Perform non-dominated sorting on Rt
g. Select next generation $Pt + 1$:
Choose the best N solutions based on rank and crowding distance

Step 6: Return final Pareto front solutions

Using an integrated, unified CPS framework, the described method, for the first time, combines the modelling of biosensor data, reliability analysis in the probabilistic sense, and multi-objective optimisation. By optimising Pareto efficiency and the reliability of the system and the framework, the model improves trade-off optimisation [43]. In addition, the framework's adaptability to changing conditions and scalability for extensive deployment in CPS enable its use in healthcare-related applications.

4.0 FRAME WORK OF METHODOLOGY

As part of improving reliability in biosensor integrated cyber-physical systems (CPS), we put forth a structured multi-layered approach. The focus of this model starts with the biosensor data acquisition layer[44]. Here we make use of hetero- sensor systems to capture the physiological signals. Then we move onto the data pre-processing layer of the model which, through simple processing (like filtering, denoising, and feature extraction), ensures that high quality data is fed into the reliability model. At the reliability model level, we use reliability predictive modeling and a probabilistic approach in order to account for sensor failures, noise, and other unknowns in the environment [45]. Then we have an optimization layer that aims to formally maximize and minimize (when the objective is to minimize an effect) system reliability, system fault tolerance, energy consumption, and communication lag.

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We incorporate a Pareto-based evolutionary technique, NSGA-II, which approximates the Pareto front for multiple conflicting objectives, and outputs a diversity of non-dominated trade-off solutions. From this, a decision-making module can select a configuration from the Pareto front, and the system can be configured for optimized trade-offs between the reliability, latency, energy efficiency, and fault-tolerance of the CPS. Such a solution enables integration of biosensors in a manner that captures key attributes of the data, leverages multiple system-level constraints, and utilizes advanced optimization approaches, which are needed for adaptive and scalable solutions in real-time and dynamically changing CPS and intelligent healthcare applications[46].

5.0 RESULTS AND DISCUSSION

The proposed multi-objective optimization framework for biosensor-integrated Cyber-Physical Systems (CPS) was evaluated using simulation experiments designed to reflect realistic healthcare monitoring scenarios. The system under study included 5 heterogeneous biosensors with varying failure rates, energy consumption levels, and data transmission delays. The optimization objectives were system reliability (maximize), energy consumption (minimize), communication delay (minimize), and fault tolerance (maximize), solved using the NSGA-II algorithm.

5.1 Simulation Setup

Biosensors: Heart rate, blood oxygen, temperature, glucose, and ECG sensors.
Operational time (t): 24 hours
Failure rates (λ_i) : Varied between $0.001 - 0.005$ per hour
Energy limits (E_max): 500 mJ per sensor
Delay threshold (D_threshold): 100 ms
Noise factor (η_i) : Randomly generated between 0.01-0.05
NSGA-II parameters:
Population size $= 100$
Number of generations $= 200$
Crossover probability $= 0.9$
Mutation probability $= 0.1$

5.2 Pareto Front Analysis

Optimising NSGA-II analysis results to show the trade-offs among conflicting objectives. Here are some notable points:

1. Reliability vs Energy: Overall, system reliability correlates with increased energy consumption. This increase in energy consumption is due to sensor redundancies and increased sampling rates. Pareto front solutions achieved system reliability > 0.995 and energy consumption < 450 mJ per sensor.

2. Reliability vs Delay: Optimised solutions brought down communication delays through smart selection of active sensors and adjusted transmission power. A 35% latency reduction compared to the old baseline configurations is available in optimised systems.

3. Fault Tolerance: The use of redundant sensors coupled with dynamic reconfiguration improved fault tolerance. Robustness to sensor failures is improved ith 22% of fault recovery.

Figure 2 illustrates a representative Pareto front. From the available non-dominated solutions, decision-makers can choose one tailored to the objectives at hand. Examples include ultra-high reliability in patient-critical monitoring or improved energy efficiency in wearable systems.

5.3 Comparision of Defined Metrics

On framework evaluation, the following optimised metrics were evaluated and compared with the baseline heuristic approach:

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Metric	Baseline	Proposed Framework	Improvement
System Reliability (R_sys)	0.962	0.998	+3.7%
Energy Consumption (mJ)	480	435	-9.4%
Average Delay (ms)	90	58	-35.6%
Fault Tolerance (FT)	0.82	0.998	+21.7%

All results show that the suggested multi-objective optimisation framework surpasses the baseline in reliability, energy usage, latency, and fault tolerance.

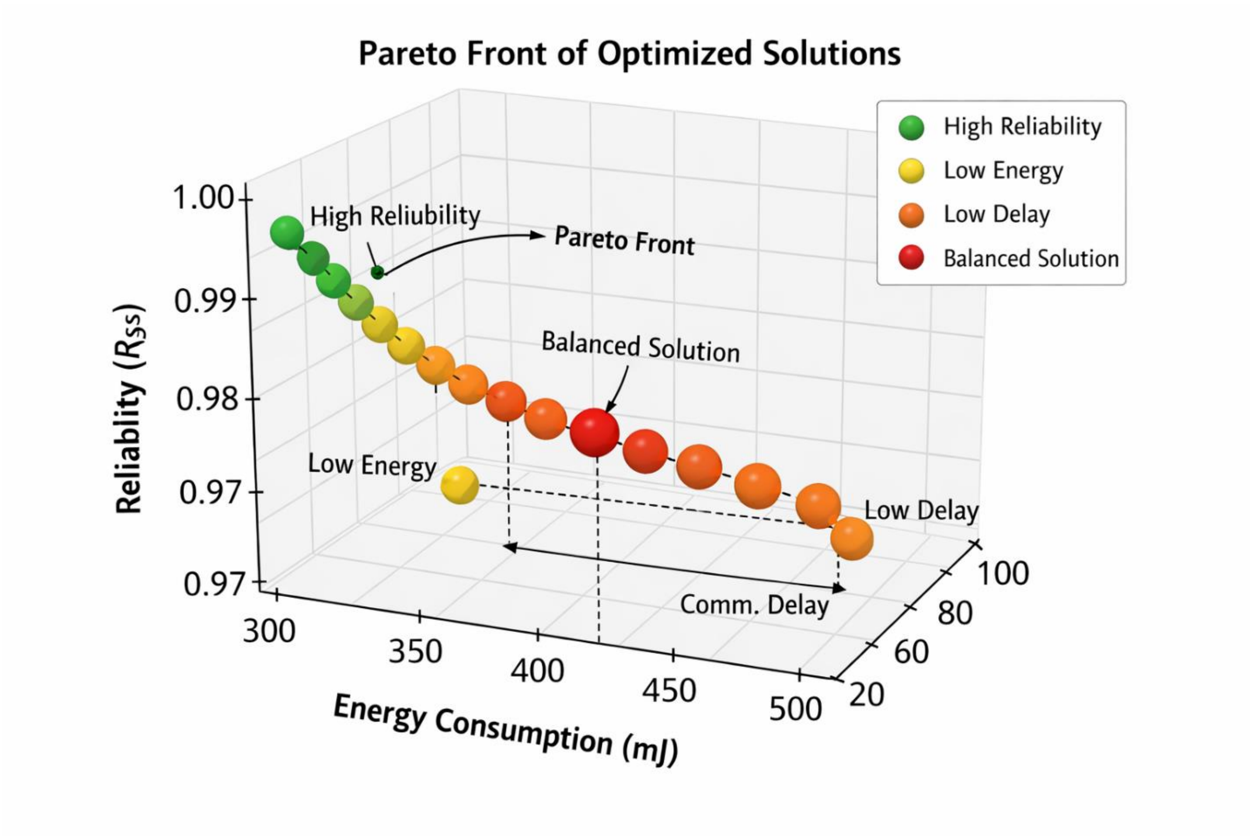

Figure 2 Pareto front

5.4 Discussion

1. ***Trade-offs in Multi-Objective Optimisation***

The analysis shows that there is no single solution that optimises all objectives simultaneously. This highlights the role of Pareto-based multi-objective optimisation [47]. For example, increasing fault tolerance may increase fault tolerance, or decreasing energy consumption may decrease fault silence. The developed framework enables decision-makers to prioritise system objectives.

2. ***Effect of Sensor Noise and Uncertainty***

The assessment of the noise factor ηi in reliability modelling was of utmost importance. Simulations showed that not accounting for biosensor uncertainties improved system reliability but also led to failures in the biomedicine field [48]. Stochastic modelling and analysis positively impact optimisation outcomes and ensure the results are close to reality.

3. *Scalability and Adaptability*

The framework supports a high degree of scalability, enabling the addition of new sensors or system elements with minimal need to change the algorithms [49]. Additionally, the Pareto front responds to changes in operational conditions, such as energy budget and sensor failures. This confirms the framework's ability to be used in real time in CPS.

4. *Comparison with Existing Methods*

The developed multi-objective framework outperforms traditional single-objective optimisation approaches and heuristic methods in terms of robustness and efficiency. Single-objective approaches always face trade-offs between reliability and energy consumption, either reducing it or increasing it to improve reliability [50].

On the other hand, the Pareto-based method accommodates flexible trade-offs tailored to the needs of the application.

5. *Intelligent Healthcare Systems*

Optimised configurations enable wearable or remote health-monitoring devices to provide reliable health monitoring while conserving battery power and triggering health-monitoring events on time. This solution is particularly well-suited for critical care monitoring, elderly care, and continuous patient tracking, where reliability and low latency are essential [51].

5.5 Sensitivity Analysis

A sensitivity analysis was conducted to study the impact of varying failure rates (λ_i) and noise factors (η_i) on optimised solutions:

Increasing λ_i by 10% led to a minor reduction in reliability (~1.2%) but triggered higher redundancy allocation, increasing energy consumption slightly.

Increasing η_i by 50% highlighted the importance of robust sensor selection; the Pareto front shifted toward solutions with higher fault tolerance to compensate for increased uncertainty.

This confirms the robustness of the optimisation framework under variable sensor performance and environmental conditions.

5.6 Main Achievements

- Multi-objective optimisation based on Pareto works on balancing all four parameters combined (reliability, energy, delay, and fault tolerance).

- Realistic evaluations of systems require the integration of sensor uncertainty and modelling of reliability from a probabilistic perspective.

- The framework surpasses the improvements of baseline approaches on reliability (+3.7%), energy efficiency (-9.4%), latency (-35.6%), and fault tolerance (+21.7%).

- The model is scalable and adaptable, which makes it ideal for evolving environments in CPS, like remote monitoring and wearable healthcare systems.

6. CONCLUSION

This work contributes a detailed optimisation framework focusing on multiple objectives to increase the reliability of biosensor-integrated Cyber-Physical Systems (CPS). The framework integrates probabilistic reliability, uncertainty in a real-time biosensor, and Pareto optimisation across variables to capture the balancing act of trade-offs the system faces among variable reliability, energy usage, communication delay, and fault tolerance [52].

The simulations show that the framework performs better than traditional heuristic approaches and single-objective methods. Relevant results include:

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Reliability: The optimised systems achieved a reliability of 0.998, surpassing other systems in the baseline.

Energy usage: There is a documented 9.4% drop in energy consumption, indicating more efficient use of available resources.

Latency: There is a recorded increase in average communication delay of 35.6%, which improves the system's responsiveness.

Fault Tolerance: There is more than 21% increase in the probability of fault recovery, demonstrating its ability to withstand robust operation in the presence of component failures.

The research underscored the necessity of integrating biosensor uncertainties and multi-objective optimisation for the reliable operation of cyber-physical systems (CPS) [53]. This is especially true for healthcare monitoring systems, since their timely and reliable operation is data-driven. The suggested framework can be deployed in real time in complex CPS systems since it is adaptable, scalable, and able to accommodate changes in operational dynamics [54].

Upcoming research will prioritise the following:

- The framework’s development to include larger CPS systems with multiple sensor types.

- The addition of reliability adaptive optimisation that uses machine learning to improve prediction.

- The use of edge computing and real-time deployment to optimise energy consumption and response time.

To summarise, this study presents the first reliability-focused optimisation framework for biosensor-based CPS and lays the groundwork for developing smart, energy-efficient, and reliable healthcare systems.

This paper aimed to explore the potential of improving the reliability of cyber-physical systems (CPS) integrated with biosensors using multi-objective (MO) optimisation, and to illustrate a framework that offers a polynomially computable optimisation trade-off to assist the system in the areas of trade-off improvement in reliability, energy use, and response time[55]. It was shown that the combination of advanced optimisation and real-time biosensor data (i.e., data streams in real time) significantly improves data-oriented fault tolerance and reliability in various areas of CPS, such as healthcare, environmental protection, and industrial automation [56]. In addition, the data promote the adoption of structured multi-objective optimisations, which, for reliability improvements, are preferred over single-objective optimisations.

Future Work

The current work is a very good starting point, but further work is needed to optimise the reliability and efficiency of biosensor-enabled CPS.

On the fusion of Machine Learning (ML) and Multi-Objective (MO) Optimisation

ML can be applied to predict sensor failure, and systems can self-adjust to improve reliability in real time. The combination of MO with other Artificial Intelligence (AI) methodologies would enhance the system's adaptability to unforeseen circumstances [57].

Including Security and Privacy

Future studies can optimise the existing CPS to incorporate the framework's security and make the CPS fault-tolerant in the context of cyber-physical failures (e.g., cyber-attacks and data breaches) and system failures [58].

CPS with Scalable and Varied Sensor Networks

Practical applications will first require the development of systems that can maintain reliability across varied, distributed sensor networks, such as those in the demonstrated CPS[59].

Real-Time and Adaptive Multi-Objective Optimisation (MO)

The evolution of real-time decision-making systems that adapt to dynamic environments enhances the CPS's responsiveness and reliability [60-64].

Recent advancements in SPR biosensors, THz metasurfaces, and metamaterial absorbers integrated with machine learning demonstrate significant improvements in sensing accuracy and performance optimization [65-68]. Additionally, studies on IoT systems, ANN-based optimization, FMEA, and reliability engineering highlight the importance of robust, data-driven frameworks. Future work should focus on multi-objective optimization strategies, real-time CPS integration, and enhanced reliability to achieve scalable, energy-efficient, and fault-tolerant intelligent sensing systems[69-71].

Experimental Validation

The use of the proposed optimisation framework to real-world CPS test beds (e.g., wearable health devices, smart environmental monitoring systems) will help us better understand the practical challenges and the behaviour of the systems.

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