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Optimizing Energy Usage on Madiun State Polytechnic Hybrid Trains Using Quadratic Programming and Genetic Algorithms

Ricto Yudi Wicaksono*, Fery Rosy Prasetyo, Fryscha Febryanti Puspitasari
Engineering Department – Madiun State Polytechnic
Madiun, Indonesia
*ricto@pnm.ac.id

Abstract – *The transportation sector remains a major contributor to global oil consumption, raising concerns related to energy security, operating costs, and environmental sustainability. Hybrid train systems that integrate catenary electricity with diesel propulsion offer an effective solution for reducing fuel usage and emissions, particularly on partially electrified rail networks. However, the coexistence of multiple energy sources necessitates robust optimization strategies to ensure efficient and cost-effective power allocation. This study presents a comparative investigation of energy management optimization in a hybrid train system developed at Madiun State Polytechnic using two distinct approaches: Quadratic Programming (QP Linear) and Genetic Algorithm (GA). The optimization objective is to minimize the total operational cost while satisfying time-varying power demand, source capacity constraints, and penalty conditions associated with load imbalance and curved track operation. The proposed formulation incorporates power balance constraints and cost-weighted energy allocation to reflect practical operating conditions. Simulation results indicate that both QP and GA converge to an identical optimal solution with a total cost of 2698.80. The optimal strategy maintains the pantograph output at approximately 114 kW, with incremental power demand supplied by the diesel engine. Increased diesel utilization is observed during curved track segments due to additional mechanical load requirements. While both methods achieve the same optimal solution, their computational characteristics differ substantially. QP Linear yields fast, deterministic, and repeatable solutions owing to the convex structure of the optimization problem, whereas GA requires a larger number of iterations but provides greater flexibility for non-linear and non-convex optimization scenarios. These findings suggest that QP is well suited for structured and real-time hybrid train energy management applications, while GA remains advantageous for complex systems involving higher degrees of non-linearity and uncertainty. The results provide practical insights for selecting appropriate optimization techniques in hybrid railway propulsion systems.*

Keywords – *Diesel; Genetic Algorithm; Hybrid Train; Pantograph; Quadratic Programming*

I. Introduction

SEVERAL sectors worldwide continue to exhibit a high dependence on oil-based energy, with the transportation sector remaining the dominant consumer. This trend is reflected in medium-term global energy outlooks, which indicate a persistent increase in oil demand. In 2024, global oil consumption reached approximately 103 million barrels per day (mb/d) and is projected to rise to around 113 million barrels per day (mb/d) by 2030 [1]. Such growth not only intensifies pressure on energy supply chains but also exacerbates price volatility and energy security risks, reinforcing oil's strategic yet vulnerable role in the global energy system.

In response to these challenges, substantial global efforts have been directed toward the electrification of transportation systems as a means to reduce dependence on fossil fuels. Among various alternatives, hybrid train technology has emerged as a practical and transitional solution, particularly for railway networks that are not fully electrified. Hybrid trains utilize more than one energy source for propulsion, typically combining electric power from overhead catenary systems or onboard batteries with conventional diesel engines [2]. This dual-energy configuration enables improved operational flexibility while offering significant reductions in fuel consumption and emissions. Beyond economic benefits, hybrid propulsion contributes to mitigating greenhouse gas emissions and local air pollutants, yielding positive impacts on environmental quality and public health, especially in partially electrified rail corridors [3].

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Despite these advantages, the presence of multiple energy sources introduces substantial challenges in energy management. Hybrid train systems require coordinated power allocation between electricity and diesel to avoid inefficiencies, unnecessary fuel consumption, and increased emissions [4]. Effective energy optimization strategies enable the prioritization of lower-cost and cleaner energy sources, such as electricity, while limiting diesel usage to conditions where it is strictly required [5]. This approach not only reduces operational costs but also minimizes exhaust emissions that adversely affect the environment [6]. Moreover, optimized energy management contributes to maintaining the performance and durability of critical components, including diesel engines and energy storage systems, thereby extending system lifespan and improving overall reliability [7]. A well-designed optimization framework also ensures smooth transitions between power sources in response to varying operational conditions, while supporting compliance with energy efficiency and environmental regulations [8].

Various optimization techniques have been explored in the literature to address hybrid train energy management. For instance, the study in [9] investigated energy management strategies for hybrid trains incorporating diesel engines, electric drives, and battery systems. Using dynamic programming (DP), the authors reported a 7.2% improvement in fuel efficiency and fuel savings of up to 22.9% compared to conventional diesel-electric locomotives. However, DP-based approaches often suffer from high computational complexity, commonly referred to as the curse of dimensionality, as well as scalability issues associated with expanding state grids [10]. These limitations restrict their applicability in real-time or large-scale operational scenarios.

Heuristic optimization methods, particularly Genetic Algorithms (GA), have also been widely applied in railway energy management problems. In [11], an improved adaptive genetic algorithm (AGA) was used to optimize train speed profiles, achieving enhanced punctuality and energy efficiency compared to conventional GA. Additional studies have demonstrated that GA-based approaches can effectively optimize speed control and battery management in DC electric train systems, resulting in power consumption reductions ranging from 15% to 30% under different operational scenarios [12]. Genetic Algorithms (GAs) are widely recognized as powerful optimization techniques for solving non-linear and complex problems. Nevertheless, a well-documented limitation of GA lies in its relatively high computational complexity, particularly when applied to large-scale or high-dimensional optimization tasks. Due to their population-based and iterative nature, GAs often require a substantial number of generations to achieve convergence, resulting in long execution times and increased computational cost.

Several studies have explicitly highlighted this drawback. Vié [13] emphasizes that GAs are frequently criticized for their computational burden, especially when handling complex optimization landscapes, and stresses the need for improved efficiency to enhance their practical applicability. Similarly, Al-oqaily and Shakah [14] report that GA-based optimization processes may consume many hours of computation, particularly when conventional serial implementations are used for non-linear optimization problems. Despite these challenges, recent research has demonstrated promising strategies to alleviate the computational limitations of GAs. Goodship et al. [15] propose a GA-accelerated optimization framework that significantly reduces convergence time. Their results show a reduction in average convergence iterations from 477 to 143, while the median number of iterations decreases from 280 to 105, indicating a substantial improvement in computational efficiency. In addition, Umbarkar [16] demonstrates that parallel implementations of GA using shared-memory architectures can significantly enhance performance by exploiting multiple computational cores, making GAs more feasible for large-scale continuous non-linear optimization problems. Overall, these findings suggest that while GAs inherently exhibit high computational complexity, ongoing developments in hybrid strategies, acceleration techniques, and parallel computing architectures have considerably improved their efficiency. As a result, GAs remain a competitive and flexible optimization approach, particularly for complex and non-convex problems where classical deterministic methods may not be suitable.

In contrast, Quadratic Programming (QP) has gained attention as an efficient alternative for hybrid energy management problems characterized by convex objective functions and linear constraints. Owing to its deterministic and convex mathematical structure, QP can deliver fast and globally optimal solutions with significantly lower computational burden compared to heuristic methods [17]. These characteristics make QP particularly attractive for structured and real-time energy management applications in hybrid transportation systems.

Based on the aforementioned discussion, this study proposes a comparative energy optimization framework for diesel hybrid trains powered by catenary electricity. The research focuses on a hybrid train system developed at Madiun State Polytechnic and investigates the performance of two optimization approaches: Genetic Algorithm (GA) and Quadratic Programming (QP Linear). The primary objective is to evaluate their effectiveness in minimizing operational cost while satisfying power demand, system constraints, and penalty conditions associated with track curvature. By providing a direct comparison between heuristic and deterministic optimization methods under identical operating conditions, this study aims to offer practical insights into selecting appropriate energy management strategies for hybrid railway propulsion systems.

II. Research Methods

The hybrid train system investigated in this study is developed at Madiun State Polytechnic and utilizes two primary energy sources, namely a diesel engine and an external electric supply from a catenary system. The overall system configuration is illustrated in Figure 1. Each energy source is connected to a switching mechanism that enables seamless operation between diesel mode and catenary mode depending on operational conditions.

As shown in Figure 1, the traction motor requires a power of 84.7 kW, while auxiliary systems consume an additional 53.07 kW, resulting in a total power demand of 137.77 kW. Given the presence of multiple energy sources with different cost and capacity characteristics, the primary objective of this study is to determine the optimal combination of catenary and diesel power that satisfies the time-varying power demand while minimizing the total operational cost, denoted by the objective function J.

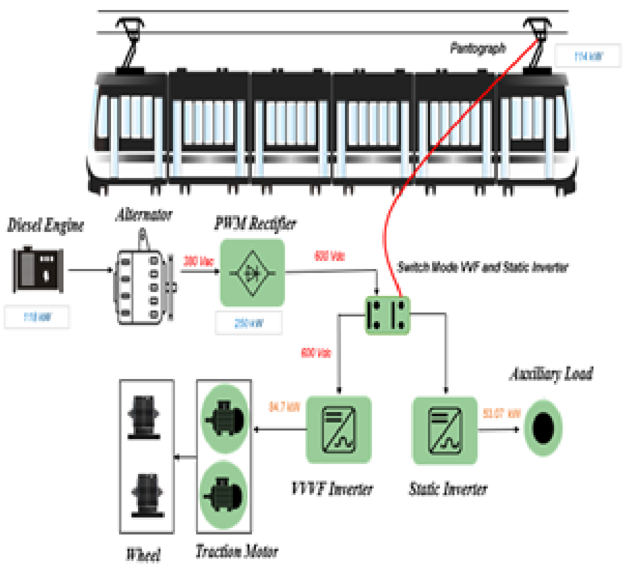

Figure 1: Hybrid train configuration at Madiun State Polytechnic

i. Optimization with Genetic Algorithm (GA)

The Genetic Algorithm (GA) is employed as one of the optimization approaches to determine the optimal power allocation between the catenary supply and the diesel engine. GA is selected due to its robustness in solving non-linear and complex optimization problems involving multiple decision variables and constraints [18].

GA operates by emulating the process of biological evolution, where each candidate solution is encoded as an individual within a population. Through iterative processes of selection, crossover, and mutation, the population evolves toward improved solutions that progressively minimize the objective function [19]. In this study, the optimization objective is to minimize the total energy cost over the operating horizon, which is mathematically formulated in Equation (1).

$$J = \sum_{t=1}^{N} \left(c_c P_c(t)^2 + c_d P_d(t)^2 \right) \tag{1}$$

As expressed in Equation (1), the total cost J is computed as the weighted sum of squared power contributions from the catenary and diesel sources over N discrete time steps. The coefficients c_c and c_d represent the cost factors associated with catenary and diesel energy, respectively, reflecting their relative economic and environmental impacts.

To ensure physical feasibility, the optimization problem is subject to a power balance constraint, which enforces that the combined power supplied by both sources must meet the required load demand at each time step. This condition is defined in Equation (2).

$$P_c(t) + P_d(t) = P_{dem}(t), \quad \forall t = 1, \ldots, N \tag{2}$$

In addition to power balance, each energy source is constrained by its maximum available capacity. These operational limits are imposed through the inequality constraints given in Equation (3).

$$0 \le P_c(t) \le P_{c,\max}, \quad 0 \le P_d(t) \le P_{d,\max} \tag{3}$$

In Equations (2) and (3), $P_c(t)$ denotes the power supplied by the catenary at time t, $P_d(t)$ represents the diesel engine power, and $P_{dem}(t)$ is the total power demand of the train.

For implementation within the GA framework, the objective function in Equation (1) is reformulated as a fitness function that maps each candidate solution to a scalar value, as shown in Equation (4).

$$f(X) = J(X) \tag{4}$$

However, GA does not inherently guarantee strict satisfaction of constraints. Therefore, to penalize infeasible solutions that violate the power balance condition in Equation (2), a penalty term is incorporated into the fitness function. The resulting penalized fitness function is defined in Equation (5).

$$f(X) = J(X) + \lambda \sum_{t=1}^{N} |P_c(t) + P_d(t) - P_{dem}(t)| \quad (5)$$

In Equation (5), λ denotes a large penalty coefficient that discourages solutions violating the power balance constraint.

During the evolutionary process, new candidate solutions are generated using a crossover operator, which combines information from two parent solutions. The crossover operation adopted in this study is expressed in Equation (6).

$$X_{child} = \alpha X_{parent1} + (1-\alpha) X_{parent2} \quad (6)$$

Based on the objective function in Equation (1), the constraints in Equations (2) and (3), and the penalty formulation in Equation (5), the GA-based optimization problem can be compactly expressed as shown in Equation (7).

$$\begin{aligned} \min_{P_c, P_d} \quad & \sum_{t=1}^{N} \left(c_c P_c(t)^2 + c_d P_d(t)^2 \right) \\ & + \lambda \sum_{t=1}^{N} |P_c(t) + P_d(t) - P_{dem}(t)| \end{aligned} \quad (7)$$

The optimization in Equation (7) is performed subject to the capacity constraints defined in Equation (3), ensuring that the resulting power allocation is both economically optimal and physically feasible.

ii. Optimization with Quadratic Programming (QP)

Quadratic Programming (QP) is adopted as a deterministic optimization approach for hybrid train energy management due to its effectiveness in solving problems characterized by a quadratic objective function and linear equality and inequality constraints [20]. A key advantage of QP lies in its convex mathematical structure, which guarantees fast convergence toward a globally optimal solution when the problem is properly formulated.

In its standard form, the QP problem minimizes a quadratic cost function expressed in terms of the decision vector x, as defined in Equation (8).

$$\min_{x} \quad \frac{1}{2} x^T H x + f^T x \quad (8)$$

As shown in Equation (8), the matrix H represents the Hessian of the quadratic cost function, while the vector f contains linear cost coefficients. The optimization process is subject to linear equality and inequality constraints, which ensure physical feasibility and operational limits, as formulated in Equation (9).

$$A_{eq} x = b_{eq}, \quad Ax \leq b \quad (9)$$

For the hybrid train system considered in this study, the most fundamental equality constraint is the power balance condition. This constraint enforces that, at each discrete time step, the total power supplied by the catenary and diesel sources must exactly match the power demand of the train. This requirement is mathematically expressed in Equation (10).

$$P_c(t) + P_d(t) = P_{dem}(t), \quad \forall t = 1, \ldots, N \quad (10)$$

In addition to power balance, each energy source is bounded by its respective capacity limits. These operational constraints prevent overloading of the catenary system or the diesel engine and are imposed through the inequality constraints defined in Equation (11).

$$0 \leq P_c(t) \leq P_{c,\max}, \quad 0 \leq P_d(t) \leq P_{d,\max} \quad (11)$$

To facilitate implementation within the QP framework, all optimization variables are stacked into a single decision vector, as presented in Equation (12). This formulation allows the optimization problem to be solved efficiently using standard QP solvers.

$$x = \begin{bmatrix} P_c(1) \\ P_c(2) \\ \vdots \\ P_c(N) \\ P_d(1) \\ P_d(2) \\ \vdots \\ P_d(N) \end{bmatrix} \quad (12)$$

Given the quadratic nature of the objective function, the Hessian matrix H takes a diagonal block structure, as defined in Equation (13). This structure reflects the independent contribution of catenary and diesel power costs across all time steps.

$$H = \begin{bmatrix} 2c_c I_N & 0 \\ 0 & 2c_d I_N \end{bmatrix} \quad (13)$$

In Equation (13), I_N denotes an $N \times N$ identity matrix, while c_c and c_d represent the cost coefficients associated with catenary and diesel energy, respectively. The equality constraint matrix and corresponding vector are then constructed to enforce the power balance condition in a compact matrix form, as shown in Equation (14).

$$A_{eq} = \begin{bmatrix} I_N & I_N \end{bmatrix}, \quad b_{eq} = P_{dem} \quad (14)$$

The influence of track geometry on power demand is also considered in the optimization process. As illustrated in Figure 2, the hybrid train operates along a route that includes several curved track segments. These segments introduce additional mechanical load, which is subsequently modeled as a penalty factor in the optimization formulation.

Figure 2: Hybrid train turning at Madiun State Polytechnic

iii. Specification of Hybrid Train Optimizing

The optimization of energy distribution in the hybrid train system requires a comprehensive set of input parameters that describe technical characteristics, component capacities, and cost and penalty factors. These parameters serve as the foundation for constructing both the QP and GA optimization models. The complete set of specifications employed in this study is summarized in Table 1.

As shown in Figure 2, the presence of curved track segments along the train route motivates the inclusion of turning-related penalty factors in the optimization process. The corresponding turning steps and penalty values are explicitly listed in Table 1 and incorporated into the objective function to reflect increased energy demand during curve negotiation.

Based on Table 1, the hybrid train optimization model is designed by considering key operational elements, including energy source capacities, load characteristics, and relative cost weights. The power demand varies from 100 to 200 kW across discrete time steps. The primary electric supply is provided by the pantograph, with a maximum capacity of 114 kW, while the diesel engine supplies up to 118 kW. In addition, the alternator and DC bus are rated at 250 kW, ensuring sufficient margin for power distribution from both sources.

The total operating load comprises a traction motor load of 84.7 kW and an auxiliary load of 53.07 kW, resulting in an average power demand of approximately 137.8 kW. From a cost perspective, the pantograph is assigned the lowest cost coefficient due to its higher efficiency and lower environmental impact, whereas diesel energy is penalized with a higher cost coefficient reflecting its fuel consumption and emissions.

Furthermore, the optimization model incorporates penalty factors to address power imbalance ($\alpha = 5$) and additional energy demand during curved track segments ($\beta = 20$), which occur at time steps 3, 5, 7, and 9, as specified in Table 1. Using these specifications, both the QP and GA frameworks aim to identify the optimal combination of pantograph and diesel power that meets the required demand while minimizing total cost and respecting all operational constraints.

The resulting optimal power allocation obtained using the QP approach is visualized in Figure 3, which illustrates the load-sharing behavior between the pantograph and the diesel engine across all time steps.

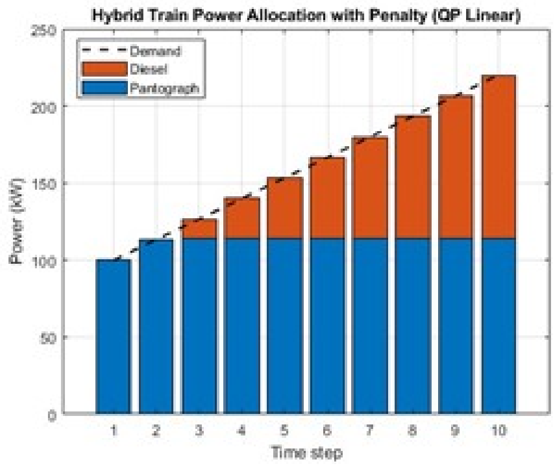

Figure 3: Optimization results of the hybrid train using Quadratic Programming (QP)

III. Results and Discussion

This section discusses the optimization results of the hybrid train propulsion system that integrates catenary electricity and diesel power. Two optimization approaches are evaluated, namely Quadratic Programming (QP), which represents a deterministic and convex optimization method, and the Genetic Algorithm (GA), which is a heuristic approach inspired by evolutionary processes. The comparison emphasizes not only the final optimal cost values but also the resulting power allocation patterns, convergence characteristics, computational efficiency, and the practical implications of each method when applied to hybrid train energy management.

i. Results of Quadratic Programming Optimization

The optimization results obtained using the Quadratic Programming (QP Linear) approach are summarized

Table 1: Hybrid Train Optimization Specifications

Components	Symbol / Variables	Value and Units
Number of time steps	N	10
Load demand	P_{dem}	100–200 kW (linear per step)
Pantograph capacity	$P_{p,\max}$	114 kW
Diesel engine capacity	$P_{d,\max}$	118 kW
Alternator capacity	–	250 kW (380 Vac–600 Vdc)
DC bus limit	$P_{bus,\max}$	250 kW
Traction motor load	–	84.7 kW
Auxiliary load	–	53.07 kW
Pantograph cost	C_p/C_c	1 (cheaper)
Diesel cost	C_d	3 (more expensive)
Load penalty factor	α	5
Turning penalty factor	β	20
Turning steps	$Curve\_steps$	[3, 5, 7, 9]
QP optimization variables	$Z = [P_p, P_d]$	$2N$ variables
GA optimization variables	P_c	N variables

in Table 2. The table presents the optimal power distribution between the pantograph and the diesel engine across ten discrete time steps. These results directly reflect the objective function formulation and constraints described in Section II, particularly the cost minimization strategy and the capacity limits of each energy source.

As shown in Table 2, during the initial operating stages (steps 1 and 2), the entire power demand is supplied solely by the pantograph, with no contribution from the diesel engine. This outcome indicates that the optimization algorithm prioritizes the utilization of the catenary system due to its lower associated cost coefficient. The pantograph power increases from 100 kW to approximately 113.33 kW as the load demand rises, remaining within its maximum allowable capacity.

From step 3 onward, the pantograph output reaches its upper limit of 114 kW and remains constant for the remainder of the operating horizon. Any additional power demand beyond this limit is supplied by the diesel engine, whose contribution increases progressively from 12.67 kW at step 3 to 106 kW at step 10. This behavior highlights the role of the diesel engine as a supplementary power source that compensates for increasing load demand and operational constraints, particularly during curved track segments.

The influence of penalty factors is also evident in the optimization outcome. As described in the problem formulation, additional penalties are imposed to account for load imbalance and curved track operation. These penalties contribute 69.47 and 80.00, respectively, to the total cost. Consequently, although the base cost function value without penalties is 2549.33, the final optimized cost reaches 2698.80. The exit flag value of 1 confirms that the QP solver successfully converged to a feasible and optimal solution under the defined constraints.

Table 2: Hybrid Train Optimization Results Using QP

Step	Optimal Pantograph Power (kW)	Optimal Diesel Power (kW)
1	100.000	0.000
2	113.333	0.000
3	114.000	12.667
4	114.000	26.000
5	114.000	39.333
6	114.000	52.667
7	114.000	66.000
8	114.000	79.333
9	114.000	92.667
10	114.000	106.000
Cost function (without penalty)	2549.33	
Penalty load	69.47	
Penalty curve	80.00	
Total cost J_{total}	2698.80 (exitflag = 1)	

From an operational perspective, the resulting power allocation strategy ensures that electrical energy from the catenary is maximized whenever possible, while diesel energy is utilized only to meet excess demand. This behavior aligns with practical energy management objectives in hybrid railway systems, where minimizing diesel usage is desirable due to its higher cost and environmental impact. Moreover, the smooth transition between energy sources across time steps demonstrates that the QP-based optimization produces stable and physically meaningful solutions suitable for real-world implementation.

The QP results also provide a valuable benchmark for evaluating the performance of heuristic optimization methods. Since the problem formulation is convex, the solution obtained via QP can be c

ii. Optimization with Quadratic Programming

The power allocation results obtained using the Quadratic Programming (QP Linear) method are summarized in Table 2. The results clearly demonstrate how the optimization framework prioritizes the utilization of catenary electricity as the primary energy source whenever sufficient capacity is available. During the initial operating stages (steps 1 and 2), the entire power demand is supplied solely by the pantograph, indicating that the optimization process favors lower-cost and more energy-efficient electric power over diesel usage under moderate load conditions.

As the power demand increases beyond the pantograph capacity, the optimization strategy transitions to a mixed-energy operation. From step 3 onward, the pantograph output reaches its maximum allowable limit of approximately 114 kW and remains constant for the remainder of the operating horizon. Any additional demand is progressively supplied by the diesel engine, whose contribution increases in proportion to the load demand. This gradual increase in diesel power reflects an economically optimal load-sharing mechanism, where diesel energy is used only when the electric supply constraint is reached.

The observed power allocation pattern is further influenced by the presence of curved track segments, as illustrated in Figure 2. Starting from step 3, curve-related penalty factors are incorporated into the optimization model to represent additional mechanical load during turning maneuvers. As a consequence, higher diesel power is required to compensate for the increased resistance and traction demand. Despite these additional constraints, the combined power output from the pantograph and diesel engine closely follows the required demand profile, confirming that the QP solution remains feasible and well aligned with system limitations.

From a cost perspective, the base objective value obtained from the quadratic cost function without penalty terms is 2549.33. When penalty components associated with load imbalance and curved track operation are included, the total cost increases to 2698.80. The exit flag value of 1 reported in Table 2 confirms that the QP solver successfully converged to a feasible and globally optimal solution. These results highlight the robustness and reliability of the QP-based optimization approach in handling both operational constraints and penalty-based cost adjustments within a deterministic framework.

The QP results also serve as an important benchmark for evaluating heuristic optimization methods. Since the problem formulation is convex and the solution obtained by QP is globally optimal, it provides a reliable reference for assessing the convergence accuracy of the Genetic Algorithm (GA) approach. In the following subsection, the convergence behavior of GA is examined and compared against this deterministic benchmark.

Table 3: Sample Optimization Progress from Generation 331 to 345

Generation	Best Function Count	Mean $f(x)$	Stall $f(x)$
331	63100	2699	0
332	63290	2699	1
333	63480	2699	0
334	63670	2699	1
335	63860	2699	0
336	64050	2699	0
337	64240	2699	1
338	64430	2699	2
339	64620	2699	3
340	64810	2699	0
341	65000	2699	1
342	65190	2699	0
343	65380	2699	0
344	65570	2699	0
345	65760	2699	1

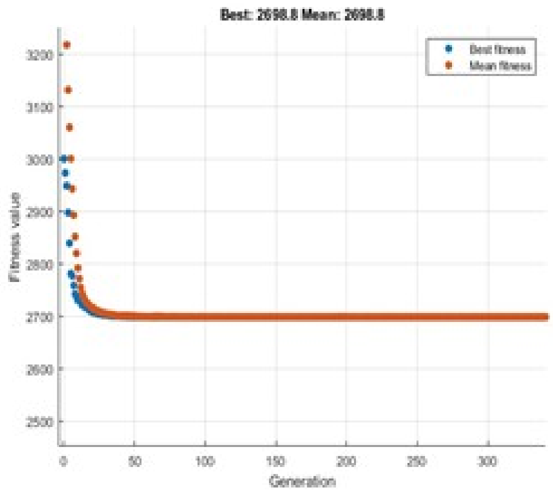

Figure 4: Convergence graph using Genetic Algorithm

iii. Optimization with Genetic Algorithm

The optimization process using the Genetic Algorithm (GA) exhibits a clear and well-defined convergence pattern. As reported in Table 3, both the best fitness value and the mean fitness value stabilize at approximately 2699 starting from generation 331. This stabilization indicates that the evolutionary process has reached an optimal solution region, where subsequent generations no longer yield significant improvements in the objective function. The consistency between the best and mean fitness values further suggests that the solution population has converged uniformly, reducing the likelihood of premature convergence to a local optimum.

This convergence behavior is further illustrated in Figure 4. In the early stages of the optimization process, a rapid reduction in the fitness value is observed, reflecting GA's strong global search capability and its effectiveness in exploring the solution space through selection, crossover, and mutation operations. As the number of generations increases, the rate of fitness improvement gradually decreases, and the convergence curve begins to flatten. This transition from rapid improvement to gradual stabilization indicates a shift from exploration to exploitation, where the algorithm refines promising solutions to approach optimality.

The optimal power allocation obtained using GA is summarized in Table 4. The resulting distribution shows that the pantograph supplies the entire power demand during the initial operating stages and continues to operate at its maximum capacity of approximately 114 kW once that limit is reached. Beyond this point, the diesel engine incrementally provides the remaining power required to satisfy the increasing load demand. This load-sharing pattern demonstrates that GA successfully captures the operational constraints and cost structure of the hybrid train system.

From a cost perspective, the GA-based optimization yields a base cost value of 2549.33 when penalty terms are excluded. When load and curve penalties are incorporated, the total cost increases to 2698.80, which is consistent with the converged fitness value observed in Table 3 and the convergence trend shown in Figure 4. The resulting hybrid train power distribution is further visualized in Figure 5, which highlights the smooth transition between pantograph and diesel power across all time steps.

Overall, these results confirm that the Genetic Algorithm is capable of producing a stable and physically meaningful optimal solution for the hybrid train energy management problem. Although the convergence process requires a relatively large number of generations, the final solution satisfies all system constraints and achieves the same optimal cost value as the deterministic approach, demonstrating the effectiveness of GA for this optimization task.

Table 4: Hybrid Train Optimization Results Using GA

Step	Optimal Pantograph Power (kW)	Optimal Diesel Power (kW)
1	100.000	0.000
2	113.333	0.000
3	114.000	12.667
4	114.000	26.000
5	114.000	39.333
6	114.000	52.667
7	114.000	66.000
8	114.000	79.333
9	114.000	92.667
10	114.000	106.000
Cost function (without penalty)	2549.33	
Penalty load	69.47	
Penalty curve	80.00	
Total cost J_{total}	2698.80	

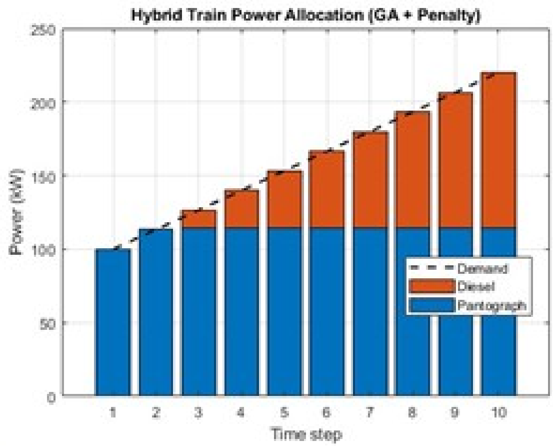

Figure 5: Hybrid train optimization results using Genetic Algorithm

IV. Conclusion

This study presents a comparative evaluation of Genetic Algorithm (GA) and Quadratic Programming (QP Linear) methods for optimizing power allocation in hybrid train systems that integrate catenary electricity and diesel propulsion. The proposed optimization framework aims to minimize operational cost while satisfying power demand, system capacity constraints, and penalty conditions associated with curved track operation. Simulation results demonstrate that both optimization approaches converge to an identical optimal solution, yielding a total cost of 2698.80 and exhibiting the same power distribution pattern. In both cases, the pantograph operates close to its maximum capacity, while the diesel engine supplies additional power as demand increases, particularly during curved track segments.

Although the final solutions obtained by GA and QP are numerically identical, the two methods differ substantially in terms of their computational characteristics and optimization mechanisms. QP Linear exploits the convex structure of the problem to achieve the optimal solution in a fast, deterministic, and repeatable manner, making it highly suitable for real-time or structured energy management applications. In contrast, GA relies on stochastic evolutionary processes and requires several hundred generations to converge, resulting in higher computational effort. However, this iterative nature allows GA to offer greater flexibility in handling non-linear, non-convex, or highly constrained optimization problems that may not be easily addressed using classical mathematical methods.

From an engineering perspective, the results confirm that effective energy management in hybrid train systems can be achieved by prioritizing the use of external electric power while employing diesel energy only when necessary to meet excess demand. This strategy not only minimizes operational cost but also aligns with broader objectives related to energy efficiency and emission reduction. The consistency between the solutions obtained using GA and QP further validates the robustness of the proposed optimization model under realistic operating conditions.

Future research may extend the current framework by incorporating additional energy storage components, such as batteries or supercapacitors, to enhance system flexibility and regenerative energy utilization. Moreover, the application of advanced optimization techniques and real-time control strategies could be explored to address dynamic operating conditions, uncertainties, and larger-scale railway systems. These extensions would further strengthen the applicability of the proposed approach to next-generation hybrid and intelligent railway propulsion systems.

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