

Article

Load-Sharing Optimization of Parallel Marine Diesel Generators Using Differential Evolution Algorithm

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Abstract

Efficient load sharing among parallel marine diesel generators enables the minimization of fuel consumption and improves the operational efficiency of shipboard power systems under variable loading conditions. This study presents a Differential Evolution (DE)-based optimization framework for load distribution in a marine AC power system consisting of six MAN 8L21/31 diesel generators while operating in parallel. Polynomial regression models of specific fuel consumption were developed using manufacturer performance data and testbed measurements, enabling accurate fuel-consumption prediction over the entire operating range. Two operational strategies were investigated: continuous manual operation with six generators online and automatic generator activation controlled by the Power Management System (PMS) according to predefined loading thresholds. The optimization objective was to determine the optimal generator load distribution that minimizes total fuel consumption while satisfying operational constraints. The results show that asymmetric load sharing can provide measurable fuel savings compared with conventional equal load distribution. In manual-operation mode, the proposed optimization achieved fuel-consumption reductions, particularly within certain system load ranges. Under PMS-controlled automatic activation, the optimization produced segmented operating regions with peak fuel savings exceeding relative reductions at medium load levels. The optimized operating strategy consistently shifted generator loading toward higher system efficiency operating regions and reduced inefficient system load operation. The results obtained from this research confirm the effectiveness of evolutionary optimization methods for improving the energy efficiency of marine diesel-electric power systems. The proposed DE-based optimization framework represents a practical approach for implementation in advanced shipboard power management systems and provides a basis for further multi-objective optimization.

Keywords: marine diesel generators; load-sharing optimization; differential evolution; fuel-consumption optimization; parallel generator operation



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1. Introduction and Previous Studies

The specific fuel consumption (SFC) of diesel engines driving marine AC generators varies substantially with the engine operating range and is not constant across the full load spectrum. Minimum specific fuel consumption is typically achieved at higher load levels, whereas operation at very low leads to increased consumption and a reduction in overall system efficiency.

In practical shipboard power systems, load sharing among generators operating in parallel mode is determined not solely by the optimal operating points of individual engines but primarily by the total electrical demand and the operational requirements imposed on the system. Conventional load-sharing strategies commonly adopt either equal load distribution among parallel units or a scheme in which one generator is operated near its optimal load range while the remaining units share the residual load evenly. Additional technical constraints within the electrical power system frequently hinder operation in the optimal load region, thereby reducing overall efficiency. This challenge is particularly evident on vessels subject to highly variable electrical demands, such as container ships with fluctuating numbers of refrigerated containers or dynamically positioned vessels requiring continuous power reserve margins.

Under such operating conditions, diesel generators often run at partial or low loads, where specific fuel consumption is considerably higher relative to the full load range. This highlights the potential for optimizing power distribution among generators operating in parallel in order to reduce total fuel consumption.

The objective of this research is to develop and apply a mathematical model and optimization methods that enable efficient operation of marine AC diesel generators by means of load-sharing strategies, with the aim of improving overall energy efficiency under variable electrical load conditions. This study considers only the fuel and power characteristics of diesel engines and does not take into account the electrical aspects of load sharing, such as copper losses, relative power distribution, or other electrical performance parameters. The objective is to investigate the potential for fuel savings achieved through the optimization of prime mover operation.

Furthermore, the proposed optimization framework focuses on minimizing fuel consumption under steady-state operating conditions and does not explicitly consider practical aspects such as engine wear, maintenance requirements, or system reliability. These factors could be considered in future work to further improve the practical applicability of the proposed methodology.

Several studies in this field have been published. In the studies conducted by Kanellos et al. [1–3], optimization focused on shipboard energy management in fully electric vessel architectures. Their work aimed to develop a Power Management System (PMS) capable of coordinating energy production and consumption while accounting for economic and environmental constraints, particularly greenhouse gas emission limits. The energy management problem was formulated as a Mixed Integer Nonlinear Programming (MINLP) model and solved using the Particle Swarm Optimization (PSO) algorithm. Dynamic programming (DP) was also applied for comparison. The methodology was tested on a passenger ferry with integrated electric propulsion and realistic technical constraints. Results demonstrated that PSO achieved superior economic performance compared to DP, reducing the total operating cost of the diesel generator set by approximately 3.26% relative to non-optimized operation.

Barone et al. [4] presented a dynamic simulation and optimization framework developed in the TRNSYS environment, aimed to enhance energy efficiency and sustainability in large shipboard power systems equipped with multiple diesel generators, with the focus on cruise ship applications. The methodology determines, at each time step, the optimal combination of generators to activate and their respective partial load ratios to minimize fuel consumption and maximize generator efficiency. The case study included a shipboard micro power system comprising four diesel generators (two Wärtsilä 12V46F units rated at 14.4 MW and two 14V46F units rated at 16.8 MW), five electric refrigeration units, two auxiliary oil-fired boilers and desalination systems combining multistage flash evaporation and reverse osmosis supported by waste-heat recovery. Optimization focused on distributing

load among the generators so as to keep them operating close to their optimal continuous rating (MCR), significantly reducing inefficiencies associated with partial-load operation.

A series of studies by Martinić-Cezar et al. [5–7] investigated fuel-saving and NO_x-reduction potential through an optimization model for load distribution control on LNG carriers equipped with diesel-electric propulsion and dual-fuel diesel-electric (DFDE) engines. The model incorporates real operational data and accounts for three fuel types: natural gas, heavy fuel oil, and marine diesel oil. Weighted factors were applied to balance fuel efficiency and emissions. The results showed that optimized load distribution can reduce NO_x emissions by up to 23% and achieve consistent fuel savings across different load conditions compared with uniform generator loading.

Yiğit [8] examined generator load-sharing practices on a bulk carrier. Fuel consumption at different load levels was modeled using a quadratic polynomial derived from experimental data by Başhan et al. [9]. This enabled the calculation of total fuel consumption and greenhouse gas emissions (CO₂, CH₄, and N₂O) for different load-sharing strategies. The results indicated that when power demand is low-medium (below 15% of total capacity) or high (above 50%), emissions do not differ significantly among the examined strategies, as either one generator is sufficient or all operate simultaneously. For the medium power demands (15–50% of total capacity), load-sharing strategy becomes a dominant factor, with generator operation at higher load ratios (approaching 80%) reducing emissions by up to 22% compared with operation at 40% load.

Although these mentioned studies have addressed generator load optimization in shipboard power systems, most existing approaches have been developed for specific vessel types and operating scenarios, often incorporating ship-dependent parameters such as propulsion demand, vessel speed, fuel type or generator operating costs. In contrast, the optimization framework proposed in this study is designed more as a general approach that relies only on the electrical load demand and the operational constraints of the generators themselves. By avoiding dependence on ship-specific operational and environmental parameters, the proposed model aims to provide a flexible optimization framework that can be applied to a wide range of diesel-electric shipboard power systems while maintaining computational simplicity and practical applicability.

Furthermore, this study demonstrates the application of a new optimization approach using a Differential Evolution (DE) algorithm for optimization of load-sharing problems. This provides a practical methodology that can be readily adapted to different ship configurations without requiring extensive modifications of the optimization model.

2. Methodology

This study conducts an optimization of load distribution among identical marine AC generators driven by MAN L21/31 diesel engines. These diesel engines are widely used on commercial vessels as one of the most prevalent types of auxiliary power units in modern shipboard energy systems [10,11]. Since more generators are commonly operated in parallel to meet the variable demands of the ship's electrical network, it is justified to investigate the optimal load allocation among them across the full range of possible system loads.

The first optimization study explores the manual operation of all six generators connected in parallel. This operating mode was selected as a consistent reference case, in which the number of online generators remains unchanged over the entire load range. Although such operation is not typical for common marine power plants, it may be relevant in safety critical applications where a higher number of generators is kept online to ensure redundancy, operational reliability and continuity of power supply. Moreover, maintaining

the same number of generators eliminates the influence of generator availability as an additional variable and enables a direct comparison of different load-sharing strategies.

Subsequently, second optimization study explores operation of six generators connected in parallel with the automatic generator start/stop feature. In this case, the number of generators operating in parallel is determined by predefined load thresholds within the power management system. This reflects the actual operation of marine power systems, where generators are automatically connected or disconnected depending on the load demand.

The use of the six-generator system in both operating modes ensures consistency of the test setup and allows the influence of manual and automatic generator management strategies to be evaluated under comparable conditions.

The analysis is based on design documentation [10] and available testbed data for the MAN 8L 21/31 engine [11]. At different rated power levels, this engine exhibits varying specific fuel consumption and the resulting datasets describe the fuel consumption at individual operating points (Figure 1). The fuel-consumption curves are therefore derived from engine test data obtained at five load points, where ISO-corrected (ISO 3046-1 [12]) SFC values were measured. Such data essentially represent discrete observations, whose interpretation and further analysis require approximation using smooth mathematical functions. Therefore, a polynomial regression methodology was applied, allowing the discrete values to be converted into higher-order polynomial curves that scientifically characterize the behavior of the observed quantities as a function of engine output power (Table 1).

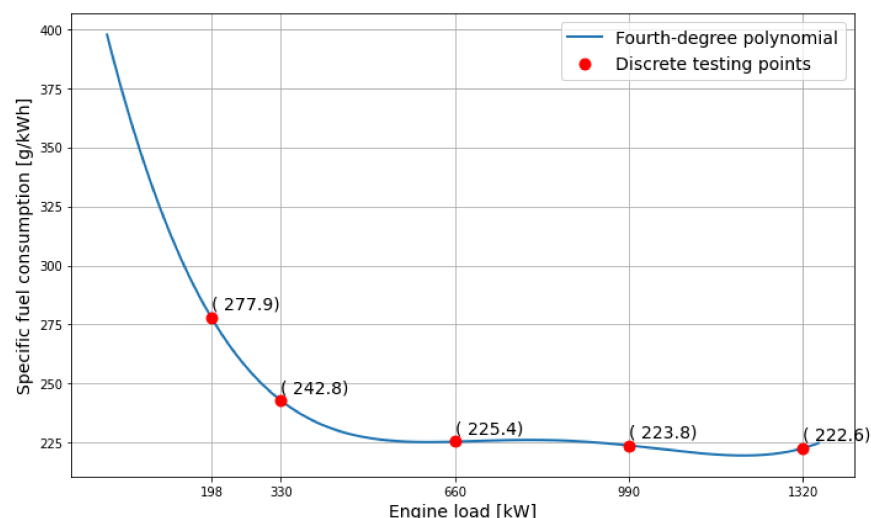


Figure 1. Test results and polynomial regression curve SFC versus load for MAN 8L21/31 engines.

Table 1. The obtained regression coefficients for the specific fuel consumption of the MAN 8L21/31 diesel engine.

Engine MAN B&W	MCR ¹ (kW)	β_4	β_3	β_2	β_1	β_0	R^2
8L21/31	1320	3.730×10^{-10}	-1.302×10^{-6}	1.635×10^{-3}	-0.880	397.584	1

¹ MCR—Maximum continuous rating.

Separate, fourth-order regression models were developed for variables of specific fuel consumption, meaning that the model includes terms up to x^4 . This polynomial order was selected because it provides excellent agreement with empirical data, evidenced by the

high coefficient of determination R^2 . This ensures that the polynomial curves accurately represent the experimental data with minimal residual error.

Therefore, a general polynomial regression model of order k can be expressed as:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_k x_i^k \quad (1)$$

where β_j (for $j = 0, 1, \dots, k$) are the regression coefficients that need to be estimated. The estimation of the parameters β_j is carried out using the least-squares method, which minimizes the sum of squared deviations between the observed values y_i and the values estimated by the model. In matrix form, the solution is obtained according to expression (2):

$$\beta = (X^T X)^{-1} X^T y \quad (2)$$

where X is the design matrix that contains the columns $[1, x_i, x_i^2, \dots, x_i^k]$ [13,14].

The quality of the model fit is evaluated using the coefficient of determination R^2 , which measures the proportion of the variability for the dependent variable explained by the regression model. The coefficient of determination R^2 is defined as the ratio between the Regression Sum of Squares (SSR) and the Total Sum of Squares (SST):

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \quad (3)$$

where SSE is the Sum of Squared Errors. The mentioned Total Sum of Squares represents the total variation in the observed values from their arithmetic mean. More precisely, SST is defined by expression (4):

$$SST = \sum (y_i - \bar{y})^2 \quad (4)$$

where y_i is the observed value of the dependent variable, and $\bar{y}$ is the arithmetic mean of observed values. The value of R^2 ranges from 0 to 1, with higher values indicating a better fit of the model to the data [15].

The applied polynomial regression methodology enables the conversion of discrete data into higher-order polynomial curves that scientifically describe how the observed quantities change as a function of engine output power. For the dependent variable of specific fuel consumption, a separate fourth-order regression model was constructed. This polynomial order was selected because it provides a very good fit to the empirical data, as indicated by high R^2 values. Therefore, this ensures that the polynomial curves accurately represent the experimental data with minimal or no residual error.

Therefore, conventional residual statistics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) or Mean Absolute Percentage Error (MAPE) do not provide additional information for these points.

Independent validation over intermediate operating points would require additional measured SFC data, which were not available in this study.

For this optimization problem a Differential Evolution (DE) algorithm was selected because the considered optimization problem is nonlinear, constrained, and may contain multiple local optima. During preliminary investigations, the Sequential Least Squares Programming (SLSQP) algorithm was also evaluated. However, its performance was found to be sensitive to the initial solution, and in several operating conditions it converged to locally optimal solutions. Consequently, a population-based global optimization method had to be adopted to improve the robustness of the complete optimization process.

Several comparative studies also have demonstrated that DE provides competitive or superior performance compared with other population-based metaheuristics algorithms, particularly in terms of robustness and solution quality. Piotrowski et al. [16] conducted

an extensive comparison of Differential Evolution and Particle Swarm Optimization (PSO) variants and reported that DE achieved better overall performance on a large number of benchmark optimization problems, particularly with respect to robustness and solution quality. Similarly, Pattanaik et al. [17] demonstrated that DE provides efficient and reliable solutions for dynamic economic load dispatch problems, indicating its suitability for complex power system optimization tasks. Furthermore, Probst et al. [18] highlighted the favorable convergence characteristics of DE, attributing its performance to an effective balance between exploration of the search space and exploitation of promising candidate solutions.

Considering the nonlinear nature of the generator fuel-consumption characteristics, the varying number of active generators and the constrained search space, DE was considered an appropriate optimization method for the load-distribution problem investigated in this study.

Differential Evolution (DE) is a stochastic, population-based optimization algorithm introduced by Storn and Price in 1997 [19]. It belongs to the family of evolutionary algorithms and is particularly effective for solving nonlinear, non-differentiable, and multimodal optimization problems. DE evolves a population of solutions through successive generations using three main operators:

1. Mutation, where new vectors are generated by adding a weighted difference in two population vectors to a third vector.
2. Crossover, where components of the mutated vector are combined with components of the current vector to form a trial vector.
3. Selection, where the trial vector replaces the current population vector if it provides a better value of the objective function.

In the following, a mathematical description of the algorithm is provided, assuming that the population contains N_p individuals, where each individual $x_{i,g}$ is a D -dimensional vector in the g -th generation, according to model (5):

$$x_{i,g} = (x_{i,g}^{(1)}, x_{i,g}^{(2)}, \dots, x_{i,g}^{(D)}) , i = 1, 2, \dots, N_p \quad (5)$$

Through mutation, a mutated vector $v_{i,g}$ is generated for each target vector $x_{i,g}$ [19], according to the rand2bin strategy, and is defined with model (6):

$$v_{i,g} = x_{r_1,g} + F[(x_{r_2,g} - x_{r_3,g}) + (x_{r_4,g} - x_{r_5,g})] \quad (6)$$

where r_1, r_2, r_3, r_4 and r_5 are mutually distinct randomly selected indices, and are also different from the target-vector index i . The parameter F represents mutation factor. In the implemented SciPy configuration, mutation dithering was used, whereby the mutation factor was randomly selected from the interval $[0.5, 1.0)$ for each generation. In the following crossover step, the trial vector $u_{i,g}^{(j)}$ is obtained by combining the donor and target vectors according to the rules:

$$u_{i,g}^{(j)} = \begin{cases} v_{i,g}^{(j)}, & \text{if } \text{rand}(0, 1) \leq C_r \text{ or } j = j_{rand} \\ x_{i,g}^{(j)}, & \text{otherwise} \end{cases} \quad (7)$$

where $C_r \in [0, 1]$ denotes the crossover probability. In the present implementation the default value $C_r = 0.7$ was used, while j_{rand} ensures that at least one component comes from the donor vector. In the subsequent selection step, the trial vector replaces the current

vector in the population if it yields a better value of the objective function, according to the principle:

$$x_{i,g+1} = \begin{cases} u_{i,g}, & \text{if } f(u_{i,g}) \leq f(x_{i,g}) \\ x_{i,g}, & \text{otherwise} \end{cases} \quad (8)$$

where $f(\cdot)$ represents the objective function.

The Differential Evolution optimization model optimizes fuel-consumption using the same underlying principles. Focusing on the fuel consumption case, for each generator i , the specific fuel consumption (SFC) represents the amount of fuel the generator uses per unit of produced energy at a given load (P):

$$SFC_i = SFC_i(P_i) \text{ where is } P_{i,min} \leq P_i \leq P_{i,max} \quad (9)$$

If the generators operate in a parallel system, the total fuel consumption (F_{total}) is expressed according to Equation (10).

$$F_{total}(P_1, \dots, P_n) = \sum_{i=1}^n P_i SFC_i(P_i) \quad (10)$$

subject to:

$$\sum_{i=1}^n P_i = P_{sys}, \quad P_{i,min} \leq P_i \leq P_{i,max} \quad (11)$$

The reduction in total fuel consumption achieved through the optimized load distribution is then expressed by Equation (12).

$$\Delta F(P_{sys}) = F_{sim}(P_{sys}) - \left(\min_{\left(\sum_{i=1}^n P_i = P_{sys}, P_{i,min} \leq P_i \leq P_{i,max} \right)} \right) F_{total}(P_1, \dots, P_n) \quad (12)$$

This optimization was implemented using the “`scipy.optimize.differential_evolution`” [20] function from the SciPy library in a Python 3.12.7 environment (Anaconda distribution), using the Spyder IDE version 5.5.1 on Windows 11 (64-bit). The optimization variables were the power outputs of the active generators, with search bounds defined as:

$$198 \leq P_i \leq 1320 \text{ kW} \quad (13)$$

The total system load P_{sys} was passed to the objective function through the argument `args=(Psys)`. Only the active generators were included in the optimization variables.

The DE algorithm was executed using the parameter settings listed in Table 2.

Table 2. DE parameter settings used within SciPy library for generator load-sharing optimization.

Parameter	Value	Description
strategy	rand2bin	Mutation and crossover strategy. A donor vector is generated using two randomly selected difference vectors added to another randomly selected vector, followed by binomial crossover.
bounds	198–1320 kW	Lower and upper limits of the optimization variables (generator power outputs) for each active generator.
args	(Psys,)	Additional argument passed to the objective function representing the required total system load.
popsiz	20	Population size multiplier. The total population consists of $20 \times N$ individuals, where N is the number of optimization variables (active generators).

Table 2. Cont.

Parameter	Value	Description
maxiter	15,000	Maximum number of generations evolved by the DE algorithm before termination if convergence has not been achieved.
mutation (F)	[0.5, 1.0)	Mutation factor (dithering). For each generation, the mutation factor F is randomly selected from the interval (0.5, 1.0), improving the balance between exploration and exploitation.
Recombination (Cr)	0.7	Binomial crossover probability. It determines the probability that a component of the donor vector replaces the corresponding component of the target vector.
tol	1×10^{-8}	Relative convergence tolerance. Optimization stops when successive improvements of the population objective values fall below this threshold.
polish	True	Enables a final local optimization using a deterministic optimizer to refine the best solution found by DE.
int	latinhypercube	Initial population generated using Latin Hypercube Sampling (LHS), providing a well-distributed coverage of the search space.
updating	immediate	The best solution is updated immediately whenever a better candidate is found during evolution.
workers	1	Optimization executed sequentially on a single processing core
Constraint handling	Penalty function	Equality constraints are incorporated into the objective function through penalty terms instead of explicit constrained optimization.
Load penalty coefficient	10^5	Penalizes solutions whose total generated power differs from the required system load.
Ordering penalty coefficient	10^6	Penalizes solutions violating the prescribed generator loading order.

The input settings define the minimum and maximum system load, the load step, generator operating limits, the selection mode (manual or automatic), and the activation thresholds for each generator. The generator selection function determines which units are running. In manual mode a predefined configuration is used. The algorithm then ensures that the total available capacity of the active generators is sufficient for the required system load, activating additional units if needed. When applying automatic generator activation through the Power Management System (PMS), predefined load thresholds determine when additional generators are started. These activation thresholds, which govern the transition between different generator configurations as system load increases, are listed in Table 3.

Table 3. Different generator load thresholds for automatic generator start within the PMS.

No. of Generators Online	Auto-Start Thresholds
1	82%
2	84%
3	86%
4	90%
5	90%

Based on the number of active generators, the corresponding input data are passed to the optimization module. This module applies the Differential Evolution algorithm to determine the optimal load distribution among the active generators while minimizing

the total fuel consumption. The fuel consumption of each generator is calculated using its mentioned polynomial fuel-consumption model, and the total fuel consumption is obtained by summing the consumption of all active generators.

To ensure that the optimization results remain physically feasible, penalty functions are incorporated into the objective function. One penalty term is applied whenever the total generated power deviates from the required system load, thereby satisfying the power balance constraint. A second penalty term is introduced to promote the predefined generator loading order. The final objective function consists of the total fuel consumption and the penalty terms, and its minimum corresponds to the optimal generator load distribution. Finally, the optimized load distribution is compared with a baseline case based on symmetric load sharing. This comparison enables the evaluation of the potential fuel savings achieved by the proposed optimization approach (Figure 2).

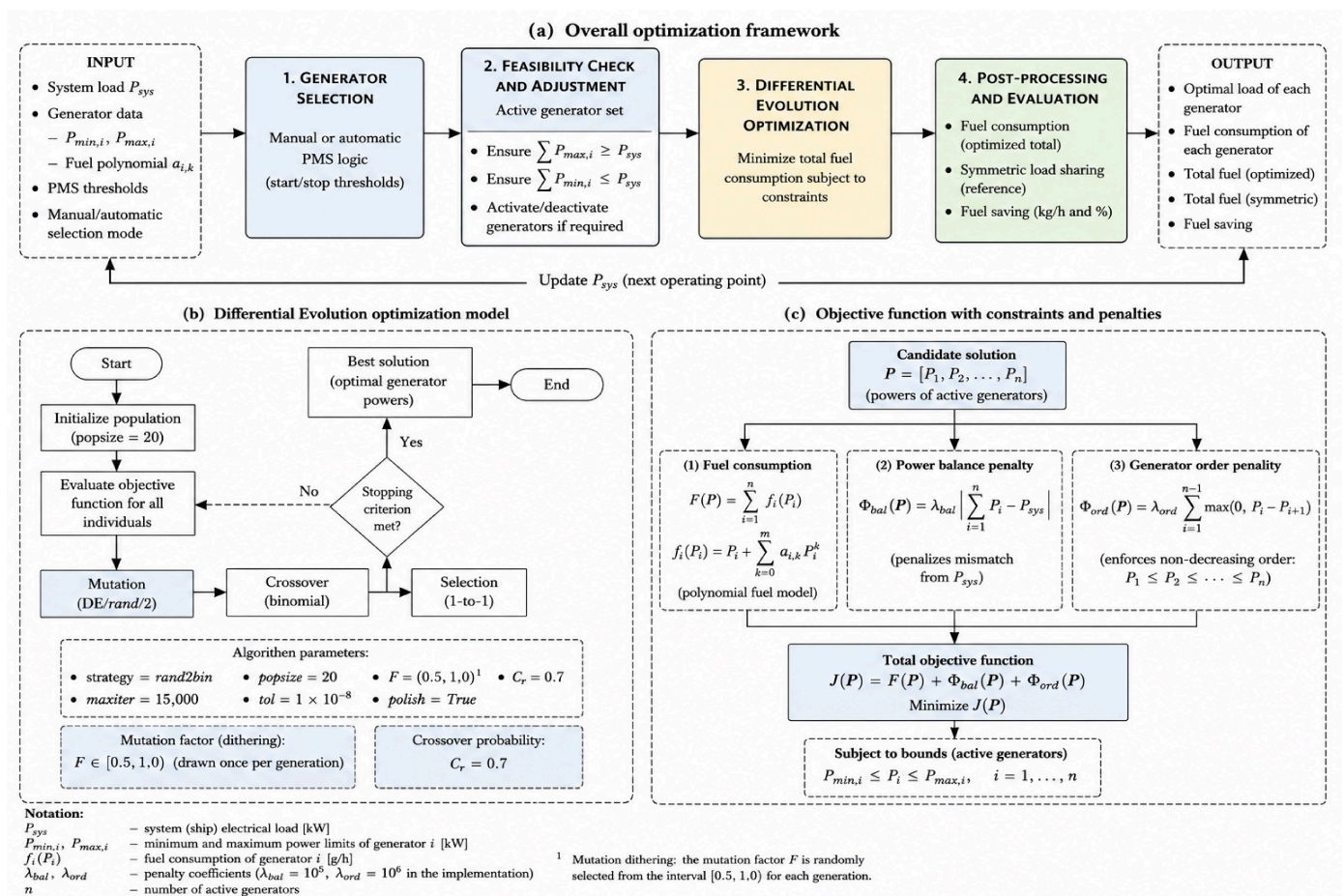


Figure 2. Overall optimization framework and DE generator load-optimization model.

3. Results

3.1. Continuous Manual Operation with Six Generators Online

The following section presents the potential fuel savings achieved by optimizing the load distribution of six parallel MAN 8L21/31 diesel generators across different shipboard power system load conditions. The engines were optimized in manual selection mode, meaning all generators were active across the entire load range, from 1188 kW up to 7920 kW. The reason for taking 1188 kW as the starting point is that the engine is not permitted to operate below 15% load (6×198 kW) when running on marine diesel fuel [10].

Figure 3 illustrates the absolute fuel-saving potential in kg/h across the full load range. The graph highlights how fuel consumption diverges between the optimal and symmetric distributions, particularly in the mid load area where generator efficiency characteristics

differ most significantly. The fuel-saving potential compared to symmetric load sharing appears primarily within the ranges from 1188 kW to 2200 kW and from 3500 kW to 7000 kW. The largest improvements are observed during transitions between different generator loading configurations. In this region, the optimization algorithm exploits the nonlinear fuel-consumption characteristics of individual generators by assigning unequal power outputs instead of enforcing perfectly symmetric load sharing. Consequently, fuel savings gradually increase from approximately 0.91 kg/h at 1288 kW to 10.99 kg/h at 4288 kW, reaching a maximum of 22.58 kg/h at a system load of 5288 kW. At this operating point, the optimized solution reduces the total fuel consumption from 1193.50 kg/h (symmetric loading) to 1170.92 kg/h, corresponding to a reduction of approximately 1.87%.

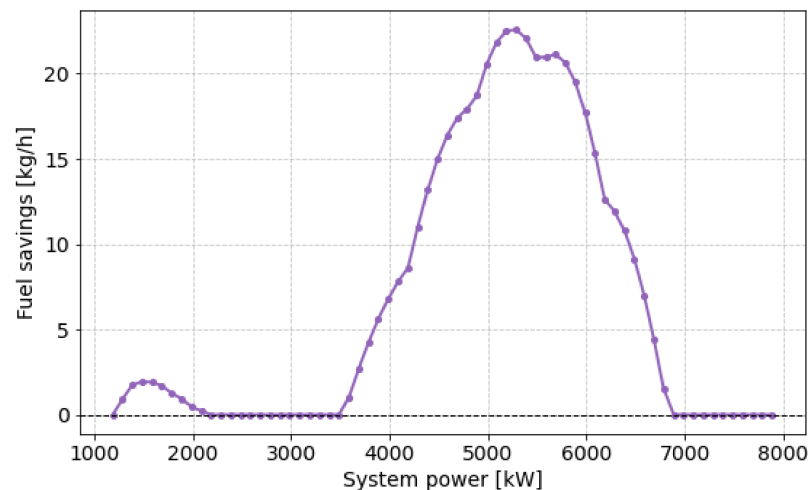


Figure 3. Comparison of potential fuel savings in kg/h between optimal and symmetric load sharing for six parallel diesel generators driven by MAN 8L21/31 engines over the entire load range of the ship's power system.

Beyond approximately 5300 kW, the achievable savings gradually decrease as the generators approach higher loading levels where their specific fuel-consumption characteristics become more similar. For example, the fuel saving decreases from 20.96 kg/h at 5488 kW to 15.31 kg/h at 6088 kW, 9.13 kg/h at 6488 kW, and only 1.47 kg/h at 6788 kW. Once all generators operate under nearly identical loading conditions (6888–7888 kW), the optimized and symmetric solutions converge again, producing virtually identical total fuel consumption. The results clearly indicate that the benefit of optimization is not uniform across the load range; instead, distinct zones emerge where the difference between optimal and symmetric load sharing becomes more pronounced.

Furthermore, Figure 4 presents the corresponding percentage fuel savings. The percentage savings closely follow the trend of the absolute fuel savings achieved through the optimized load distribution, confirming that the greatest benefits are obtained within the same operating regions. However, slightly higher percentage peaks are observed at lower load levels, as the absolute fuel consumption is relatively low in this operating region, making even modest absolute fuel savings correspond to a larger relative improvement.

Figure 5 compares the total fuel consumption obtained with the proposed optimized load sharing and the conventional symmetric load-sharing strategies over the investigated system load range. As expected, total fuel consumption increases almost linearly with increasing system power demand for both approaches.

To achieve this potential fuel-consumption saving, an optimal load allocation between generators is presented in Figure 6. This figure shows the optimized load allocation among six parallel MAN 8L21/31 generators for system loads ranging. Each colored line represents one generator.

Overall, the plot illustrates how Differential Evolution determines an optimal, non-uniform load distribution that differs significantly from symmetric sharing, leading to measurable fuel-saving benefits across various operating points.

However, since DE is a stochastic optimization algorithm, its robustness was evaluated by repeating the optimization ten times using different random seeds for three representative operating points corresponding to system loads of 4000, 6000 and 7500 kW. The same DE parameter settings were used for all runs, while only the initial random population was changed.

The results are summarized in Table 4 for investigated operating points. The optimization converged to practically identical solutions. The relative standard deviation of the total fuel consumption remained below $2.6 \times 10^{-7}\%$. These results indicate that the proposed Differential Evolution implementation is highly robust and consistently converges to the same optimum regardless of the initial random seed. Consequently, the optimization results presented in this paper are considered fully repeatable despite the stochastic nature of the algorithm.

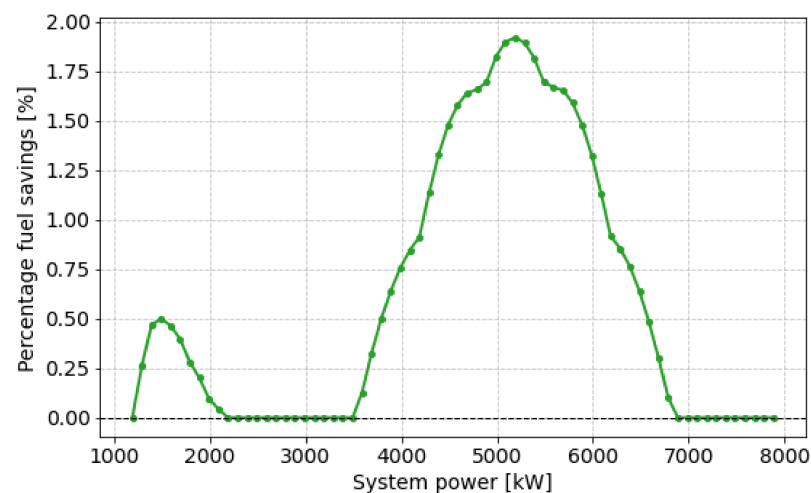


Figure 4. Potential percentage fuel savings achieved through optimized load sharing across the full range of possible ship power-system loads for six parallel diesel generators driven by MAN 8L21/31 engines.

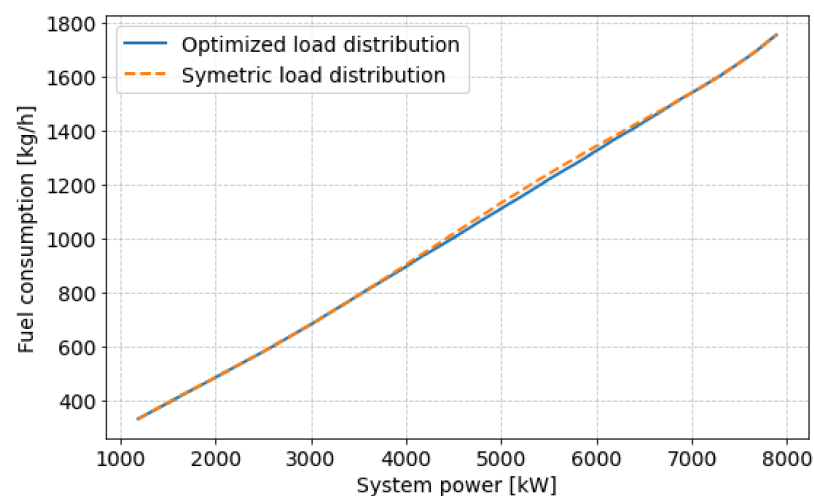


Figure 5. Comparison of fuel consumption for symmetric and optimized load sharing across the full range of possible ship power-system loads for six parallel diesel generators driven by MAN 8L21/31 engines.

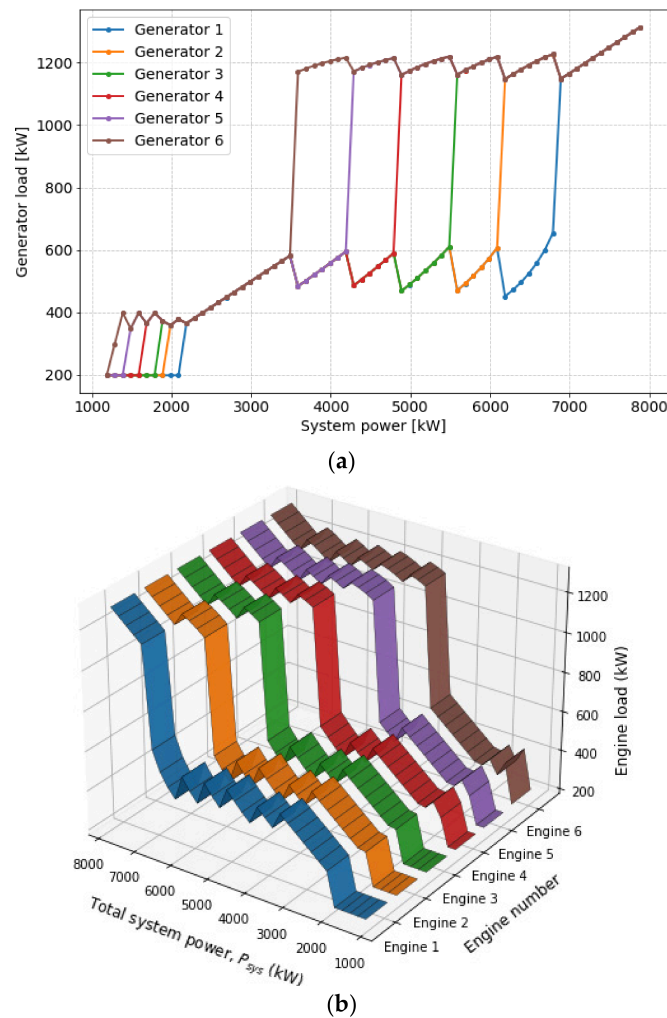


Figure 6. Fuel-optimized load distribution among the six MAN 8L21/31 diesel generators over the entire power-system load range: (a) two-dimensional representation; (b) three-dimensional representation.

Table 4. Stability analysis of the DE algorithm using 10 independent runs with different random seeds.

P_{sys} (kW)	Ind. Runs	Mean Total FC (kg/h)	Std. Dev (kg/h)	Rel. Stand. Dev. (%)
4000	10	894.829	2.3×10^{-6}	2.57×10^{-7}
6000	10	1323.920	3.14×10^{-6}	2.37×10^{-7}
7500	10	1649.270	4.19×10^{-6}	2.54×10^{-7}

To evaluate the repeatability and robustness of the proposed optimization approach, the Differential Evolution algorithm was executed ten times for each representative operating point using different random seeds. Figure 7 shows the convergence histories of the objective function value as a function of the DE generation number. Although the initial objective function values differ considerably due to the randomly generated initial populations, all runs exhibit a rapid decrease during the first generations and subsequently converge to the same objective function value. For all investigated operating points, convergence was achieved within approximately 40–60 generations, despite the maximum number of generations being set to 15,000. This indicates that the stopping criterion based on the convergence tolerance was satisfied well before the maximum iteration limit. The nearly identical final objective-function values obtained for all random seeds confirm the

robustness, repeatability, and low sensitivity of the proposed DE implementation to the initial population.

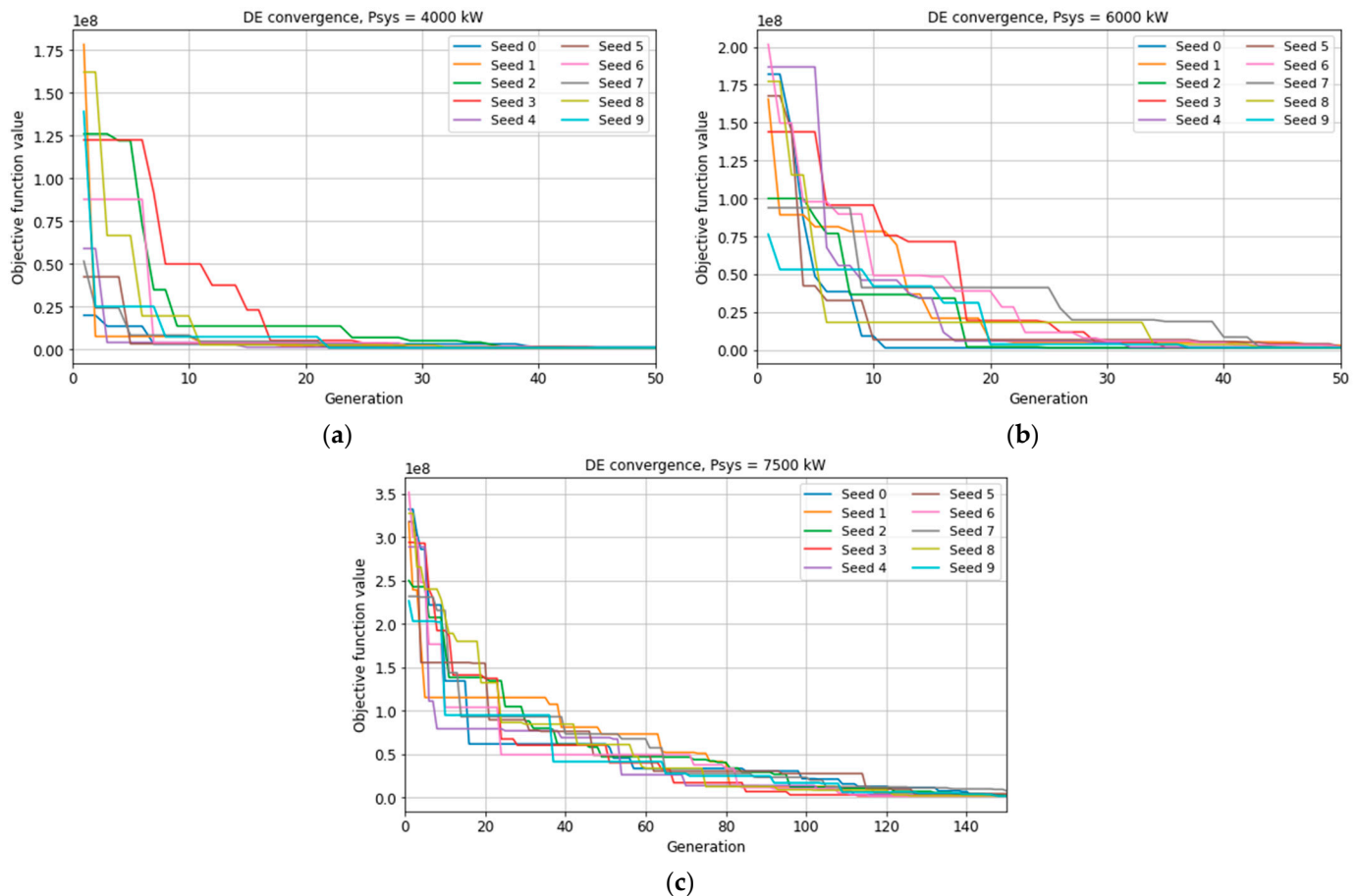


Figure 7. Convergence curves of the DE algorithm obtained from 10 independent runs with different random seeds: (a) $P_{sys} = 4000$ kW, (b) $P_{sys} = 6000$ kW, and (c) $P_{sys} = 7500$ kW.

3.2. Automatic Generator Activation Controlled by the Power Management System (PMS)

The results presented in Figures 8 and 9 demonstrate fuel-consumption savings across distinct load regions when automatic generator activation thresholds are applied within the PMS. Unlike the manual selection scenario, where all generators remain active throughout the entire load spectrum, the automatic-start function introduces stepwise transitions between generator configurations. These transitions significantly influence the achievable fuel-saving potential while using optimized load distribution.

Figure 8 shows the absolute fuel-saving potential in kg/h across the full operating range when PMS-controlled generator activation is used. The graph reveals several distinct fuel-saving zones, each corresponding to a specific number of active generators determined by PMS thresholds. Within each zone, the optimization algorithm identifies favorable load distributions that minimize fuel consumption before the next generator is automatically started. The highest savings occur in mid-load segments, particularly between approximately 3500 kW and 6000 kW, where generator efficiency characteristics differ most prominently between the optimal and symmetric strategies. Sharp drops to zero savings indicate transition points where an additional generator is activated, briefly eliminating the optimization advantage until the new operating configuration offers additional potential fuel saving.

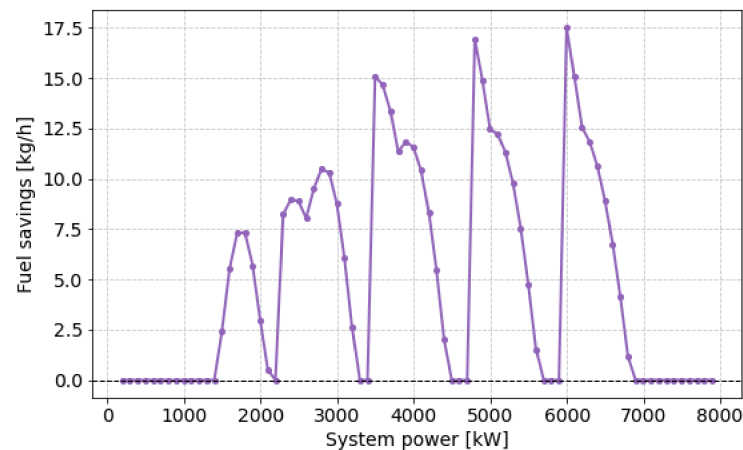


Figure 8. Potential fuel savings in kg/h between optimal and symmetric load sharing for six parallel diesel generators driven by MAN 8L21/31 engines over the entire load range of the ship's power system with PMS automatic generator-start functionality.

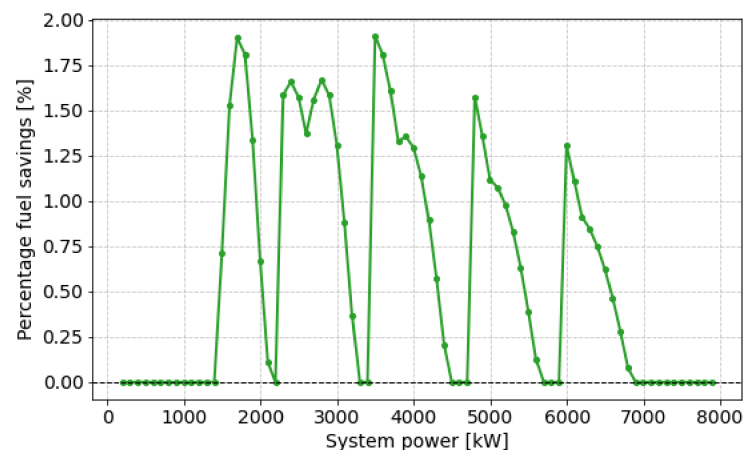


Figure 9. Potential percentage fuel savings between optimal and symmetric load sharing for six parallel diesel generators driven by MAN 8L21/31 engines over the entire load range of the ship's power system with PMS automatic generator-start functionality.

Overall, the figure highlights that the introduction of automatic-start thresholds produces a more segmented but still significant fuel-saving pattern, with peak reductions reaching up to approximately 17–18 kg/h depending on the operating point.

Figure 9 presents the percentage of fuel-saving potential achieved through optimized load sharing under PMS-controlled generator activation. The highest percentage savings occur predominantly between 1800 kW and 4200 kW, where generator loading conditions allow the optimization algorithm to significantly outperform symmetric load distribution. Within these intervals, fuel saving peaks approach or exceed 1.8%, reflecting the strong efficiency advantage of allocating load asymmetrically when only a subset of generators is operating at favorable points on their fuel-consumption curves. Similarly to the previous case, slightly higher percentage peaks are observed at lower load levels, as the absolute fuel consumption is relatively low in this operating region, making even modest absolute fuel savings correspond to a larger relative improvement.

As in the previous graph, the savings drop to zero at close to the next generator start transition points (Figures 9 and 10), where the PMS activates an additional unit. This temporary loss of optimization benefit is followed by a new 'fuel saving interval' once the next generator configuration becomes active. Toward the upper end of the load range, above 6500 kW, the potential fuel savings diminish, indicating that symmetric sharing

becomes increasingly similar to the optimal solution when all generators operate near their nominal loading.

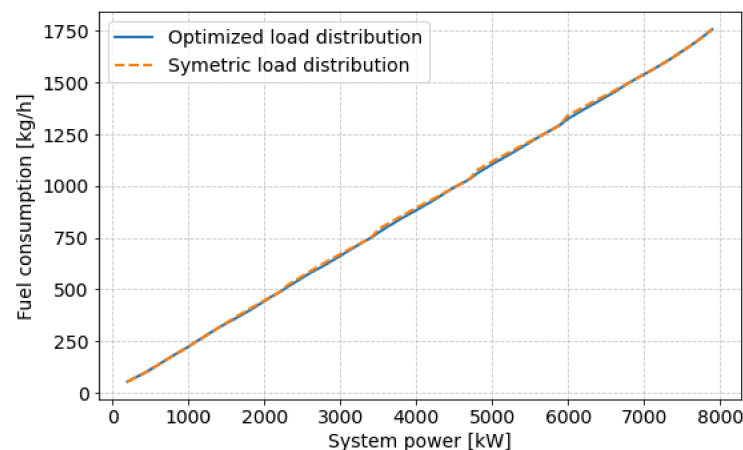


Figure 10. Comparison of fuel consumption for symmetric and optimized load sharing for six parallel diesel generators driven by MAN 8L21/31 engines over the entire load range of the ship's power system with PMS automatic generator-start functionality.

The optimized load distribution obtained under PMS automatic start is shown in Figure 11. The graph illustrates how generator loading evolves as system power increases when generator activation follows predefined PMS thresholds. At low loads, only a single generator operates, gradually increasing its output until it reaches the first PMS activation threshold. At this point, a second generator is automatically started, creating a sharp vertical transition in the load profile. The active generators then redistribute their loads according to the fuel optimization algorithm, typically resulting in one generator operating near its optimal efficiency point while the second unit remains at lower load.

As system load continues to rise, the same pattern repeats: each time a PMS threshold is exceeded, an additional generator is activated. This results in distinct vertical jumps visible in the load curves for Generators 2 through 5. Within each interval between generator activations, the optimization algorithm adjusts the loads smoothly to minimize total fuel consumption. The characteristic pattern shows one generator typically approaching its upper loading limit while the other active generators operate at lower load, reflecting the efficiency characteristics of the MAN 8L21/31 engines. Generator 6 remains inactive until the highest load range is reached. Once it comes online, all six generators contribute to supplying the final portion of the operating range, after which the load distribution gradually becomes more balanced as the system approaches its maximum power of approximately 7900 kW.

Overall, the figure demonstrates the stepwise and highly structured load distribution behavior that emerges from combining PMS automatic start thresholds with an optimization routine.

Same as in the previous case, an additional stability analysis was performed to evaluate the influence of the random initialization on the optimization results. The optimization was repeated ten times using different random seeds for five representative operating points covering the entire operating range of the power system (2000, 3500, 5000, 6500, and 7500 kW). In all cases, the automatic Power Management System (PMS) determined the number of active generators according to the predefined generator start thresholds, while all DE parameters remained unchanged. The obtained statistical results are summarized in Table 5. For all investigated operating points, the DE algorithm converged to practically identical solutions regardless of the initial random population. These results indicate that the optimization procedure is highly robust and consistently converges to the same

optimum despite the stochastic nature of the algorithm. Furthermore, only negligible differences were observed in the individual generator load allocation between independent runs, confirming that the proposed optimization methodology provides highly repeatable and reliable solutions for generator load distribution.

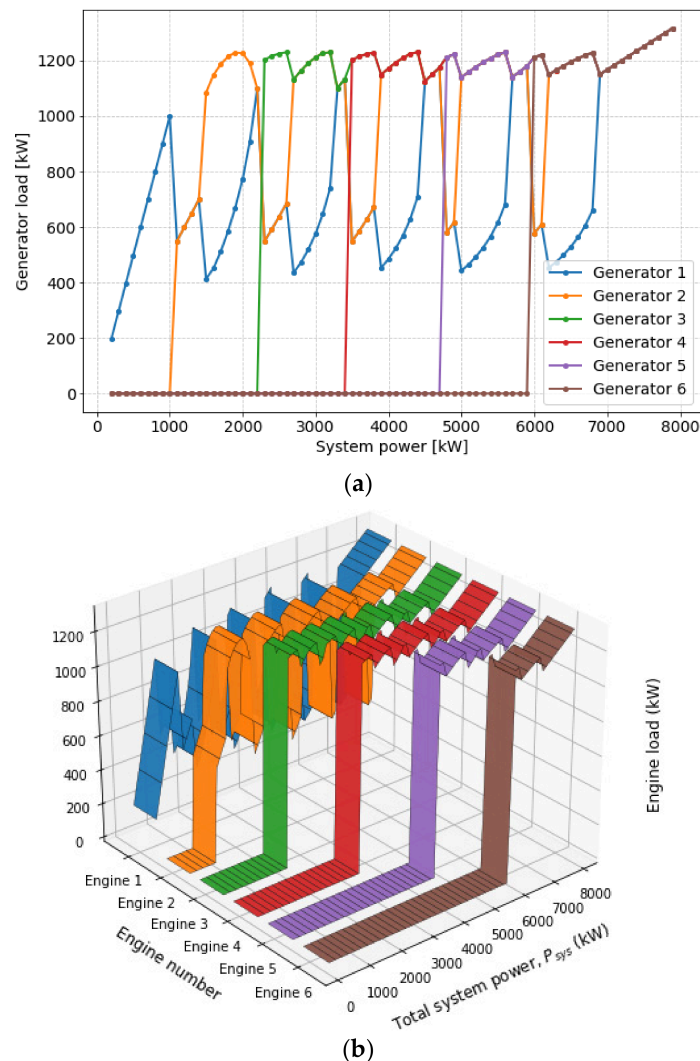


Figure 11. Optimized load distribution for six MAN 8L21/31 diesel generators across the full system power range using PMS automatic generator-start functionality: (a) two-dimensional representation; (b) three-dimensional representation.

Table 5. Stability analysis of the DE algorithm on power system with PMS auto-start feature using 10 independent runs with different random seeds.

P_{sys} (kW)	Active Gen.	Ind. Runs	Mean Total FC (kg/h)	Std. Dev (kg/h)	Rel. Stand. Dev. (%)
2000	2	10	444.208	1.26×10^{-7}	2.83×10^{-8}
3500	4	10	775.094	1.64×10^{-6}	2.12×10^{-7}
5000	5	10	1105.340	1.90×10^{-6}	1.72×10^{-7}
6500	6	10	1430.590	3.34×10^{-6}	2.33×10^{-7}
7500	6	10	1649.270	4.19×10^{-6}	2.54×10^{-7}

Figure 12 shows the evolution of the objective-function value throughout the optimization process for each operating point. Although the initial objective-function values differ significantly because of the randomly generated initial populations, all optimization runs exhibit a rapid decrease during the first generations and consistently converge to the same

final solution. The number of generations required to satisfy the convergence criterion increases with the system load, which is expected because additional generators are activated by the PMS, increasing the dimensionality of the optimization problem. Nevertheless, even at the highest investigated load of 7500 kW, all runs converge to practically identical objective-function values. These results demonstrate that the proposed Differential Evolution implementation is robust, exhibits negligible sensitivity to random initialization, and provides highly repeatable optimization results over the entire operating range of the power system.

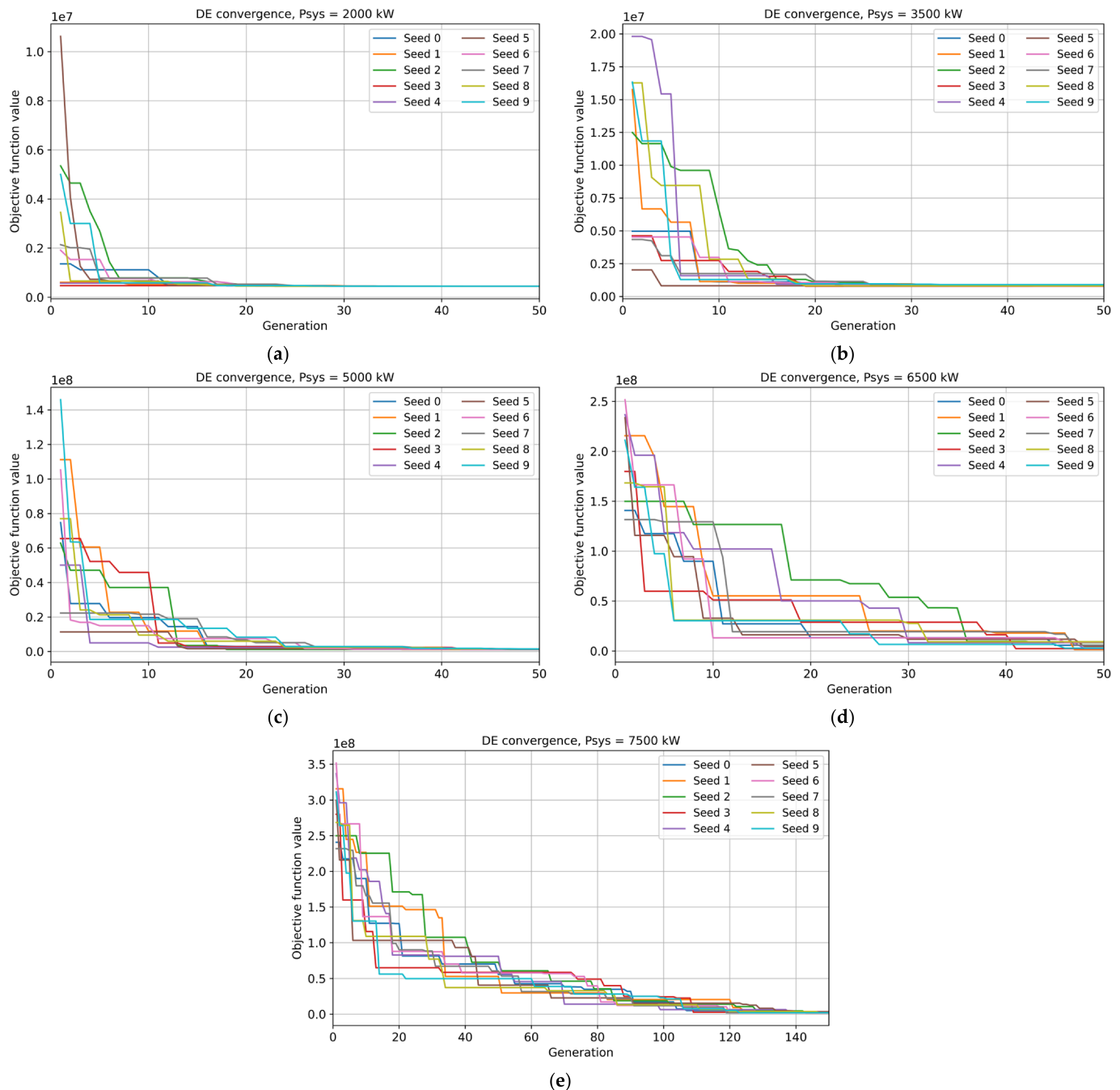


Figure 12. Convergence histories of the DE algorithm obtained from ten independent optimization runs with different random seeds under automatic PMS generator activation: (a) $P_{sys} = 2000$ kW; (b) $P_{sys} = 3500$ kW; (c) $P_{sys} = 5000$ kW; (d) $P_{sys} = 6500$ kW; and (e) $P_{sys} = 7500$ kW.

4. Discussion and Conclusions

The results obtained in this study confirm the fundamental conclusions reported in the literature: noticeable fuel-consumption reductions can be achieved by optimizing load distribution among parallel diesel generators. This is particularly noticeable when operating under variable and non-ideal loading conditions typical of shipboard power systems. The results are consistent with observations by Yiğit [8] and Bařhan et al. [9], as the analysis shows that generators operating at low or moderately loaded conditions exhibit disproportionately higher specific fuel consumption. Accordingly, strategies that shift generator loading toward higher efficiency regions yield measurable performance improvements.

Two optimization scenarios were investigated: manual selection mode, where all generators remain online across the entire load range and PMS automatic-start mode, where generators are activated according to predefined load thresholds.

In the manual selection case, the optimization algorithm had wider freedom to redistribute load among all six generators. This produced smooth, continuous load-allocation patterns and a clearer identification of efficiency “zones,” with maximum savings of 1.87%. These results align well with the findings of Martinić-Cezar et al. [5–7], who similarly demonstrated optimal, asymmetric loading where one generator operates near the optimal range while others remain at lower load. Therefore, it can reduce total fuel consumption by avoiding operation in symmetric load distribution in those load regions.

The PMS-controlled case, by contrast, introduced stepwise constraints on generator availability on potential fuel savings. The optimized load distribution therefore exhibited segmented behavior, with abrupt transitions each time a generator was automatically started. Although these constraints limited the optimizer’s freedom, fuel savings remained significant, with peak values closely matching those achieved in the manual-selection scenario. This behavior resembles the operational constraints reported by Barone et al. [4], where generator combinations were restricted by system-level activation rules, leading to optimal solutions within each feasible operating configuration.

The results are also consistent with those reported in broader optimization studies such as those of Kanellos et al. [1–3], who achieved a 3.26% reduction in operating costs. Their studies use PSO-based optimization of generator operation. While the presentable fuel savings obtained in this study (up to ~1.9%) are somewhat lower, the difference is expected because the present work optimizes only the load distribution, not generator activation scheduling, propulsion integration, or multi-energy system interactions. Furthermore, the study by Kanellos et al. considers a broader objective function, incorporating operating costs rather than focusing solely on fuel consumption.

Overall, both optimization modes confirm the principle emphasized in the literature that improved fuel efficiency can be achieved through asymmetric load distribution in some system load areas. Therefore, the electrical demand is concentrated on fewer generators operating at higher loads, rather than being evenly shared among multiple lightly loaded units. This approach minimizes prolonged low-load operation whenever feasible. The manual selection mode demonstrates the theoretical upper bound of achievable fuel savings, assuming all generators remain available for optimal load sharing, whereas the PMS-controlled mode represents a more realistic operating scenario consistent with practical shipboard safety and redundancy requirements.

In both cases, the magnitude and distribution of fuel savings closely parallel trends reported in earlier research, reinforcing the relevance and validity of the proposed optimization framework. The improved load distribution not only enhances the technical performance of the power system while respecting generator operating constraints but also has the potential to reduce operating costs through lower fuel consumption.

Although the PMS-controlled scenario improves the practical relevance of the analysis, the proposed optimization framework was evaluated exclusively through simulation under steady-state operating conditions. Consequently, transient response during generator switching, reserve-power requirements, class-specific operational requirements, and hardware implementation of the PMS were not explicitly considered. These practical aspects may influence the applicability of the optimized load distribution in real shipboard power systems and should therefore be addressed through experimental validation and testing using real ship operational profiles in future research.

As part of future research, other optimization algorithms may be evaluated using the same dataset to compare their performance in terms of solution quality and computational efficiency. Differential Evolution was selected in this study because of its proven robustness, simple implementation, and strong performance in solving nonlinear, non-convex optimization problems without requiring gradient information, making it well suited to the characteristics of the considered optimization problem.

Furthermore, the PMS activation thresholds were kept fixed throughout this study to evaluate the proposed load-optimization strategy under predefined operating conditions. Future research may investigate the joint optimization of PMS activation thresholds and generator load distribution, which could further improve the overall fuel efficiency.

Although the present study focuses on minimizing fuel consumption, the proposed optimization framework is sufficiently flexible to accommodate additional objective functions. Future research might investigate a multi-objective formulation that simultaneously considers fuel efficiency, emissions, maintenance requirements, spinning reserve, and system reliability to further improve the practical applicability of the proposed methodology.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/jmse14151349/s1>.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating Current
DE	Differential Evolution
DFDE	Dual-fuel diesel-electric
DP	Dynamic Programming
FC	Fuel consumption
ISO	International Standard Organization
LNG	Liquefied Natural Gas
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCR	Maximum Continuous Rating
MINLP	Mixed-Integer Nonlinear Programming
PMS	Power Management System
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
SFC	Specific Fuel Consumption
SLSQP	Sequential Least Squares Programming
SSE	Sum of Squared Errors
SSR	Regression Sum of Errors
SST	Total Sum of Squares

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