[1, a*] Weizhou Yang
[1,b]Ruiqing Ma
[1,c] Ziqiang Zhang

Research on Step-Down Aviation Three-Phase Power Factor Correction based on Machine Learning and Optimization Algorithm

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Abstract: - Objectives: The study looks at power quality issues, such as phase imbalance, voltage sags, and power factor issues, in aircraft systems. It highlights how immediate power factor correction steps are required to avoid equipment longevity problems and boost system efficiency, which will ultimately improve the performance of the entire aviation system.

Methodology: Using a variety of data sources, real-time data gathering, and machine learning approaches, this study focuses on data collecting and real-time monitoring in aviation systems. Predictive modeling, testing methods for data preparation and analysis, and optimization algorithms for capacitor bank size and placement are all included. Considerations for privacy and security are covered.

Result: Salp Swarm Optimization and the Dragonfly Algorithm are used in the study to assess the ideal capacitor sizes and positions, which results in better voltage profiles and lower active power losses. Aviation systems benefit from improved power factor correction through the application of integrated machine learning and optimization, which promotes sustainability and energy efficiency.

Conclusion: The study demonstrated the significance of power factor correction in aviation by successfully addressing power quality issues in aircraft electrical systems through the use of optimization algorithms for capacitor sizing and location.

Keywords: Aviation Power Factor Correction, Optimization Algorithms, Machine Learning, Electrical System Efficiency and Sustainability in Aviation

I. INTRODUCTION

Background and context of aviation power factor correction

Aviation power factor correction enhances system efficiency, reliability, sustainability. Machine learning predicts correction needs, adapting to changing electrical loads mid-flight. Farokhi (2021) The ideal size of capacitor banks is determined using optimization methods, such as genetic algorithms or particle swarm optimization and placement for step-down power factor correction. . Kumar and Zare (2019) This progressive and intelligent solution contributes to the sustainability and reliability of aviation technology, addressing the evolving needs of the aviation industry.

Significance of the research

Lee et al., (2001) The research focuses on enhancing the efficiency and reliability of aircraft systems, highlighting power factor correction as a crucial component. It aims to mitigate power quality challenges in aviation applications, such as voltage sags, phase unbalance, and power factor issues, preventing potential damage to electrical equipment and maintaining optimal system performance.

Objectives of the study

- To systematically identify and analyze power quality challenges arising from complex electrical loads within aircraft systems, including voltage sags, phase unbalance, and power factor issues.
- To emphasize the urgency of adopting power factor correction to mitigate the identified challenges and prevent adverse effects on the lifespan of electrical equipment and overall system performance.

[1] School of Automation, Northwestern Polytechnical University, Xi’an 710129 Shaanxi, China
[a]Email: yangweizhou1988@163.com
[b]Email: marq@nwpu.edu.cn
[c]Email: zhangziqiang@mail.nwpu.edu.cn
*Corresponding author: Weizhou Yang

Research question

1. What are the specific power quality challenges prevalent in aviation applications, mainly related to voltage sags, phase unbalance, and power factor issues, and how do these challenges impact the lifespan of electrical equipment and overall system performance in aircraft systems?
2. Why is power factor correction considered a vital component in enhancing the overall energy efficiency of aircraft operations, and what is the urgency in adopting power factor correction to mitigate the identified power quality challenges within the aviation domain?

Hypothesis

- The integration of machine learning and optimization algorithms in implementing step-down aviation three-phase power factor correction will significantly enhance the overall energy efficiency of aircraft operations.
- Addressing power quality challenges through power factor correction will prevent a significant reduction in the lifespan of electrical equipment and positively impact overall system performance in aviation applications.
- Machine learning for predictive modeling will result in precise estimations of power factor correction requirements, considering the dynamic and diverse electrical loads within aviation systems.
- The application of optimization algorithms, for example, particle swarm optimization or genetic algorithms, will determine the optimal capacitor bank size and placement for step-down power factor correction, contributing to intelligent and adaptive decision-making.

II. LITERATURE REVIEW

The fundamentals of power factor correction

Power quality challenges in aviation include voltage sags, phase imbalance, and power factor issues due to reactive power. Power factor correction methods include capacitor banks, synchronous condensers, and static voltage compensators (SVCs). Sarlioglu and Morris (2015) Aircraft systems have varying and complex electrical loads, including avionics, lighting, air conditioning, and other electronic components. Rosero et al., (2007) Integrating machine learning and optimization algorithms ensures adaptability to changing conditions, always learning and adjusting the power factor correction process based on real-time data and optimizing energy efficiency throughout flight operations.

Power quality issues in aviation

Voltage sags, also known as dips, are short-term reductions in voltage levels that can disrupt sensitive avionic equipment, potentially leading to malfunctions or failures. Moir and Seabridge (2011) Low power factor issues can lead to inefficient use of electrical power, increased energy losses, and reduced system capacity, resulting in higher operating costs and decreased overall energy efficiency. Austin (2011) Transient voltage events, which are sudden, brief increases in voltage, can damage electronic components and avionic systems, leading to system failures or reduced equipment lifespan. Electromagnetic interference (EMI) can disrupt the proper functioning of avionic systems, navigation instruments, and communication equipment, posing a safety risk during flight.

Power factor correction techniques like capacitor banks can mitigate reactive power. Rochlin, La Porte, and Roberts (1987) Voltage regulation uses regulators and stabilizers to maintain consistent voltage levels.

Machine learning in power factor correction

Machine learning algorithms are used to develop predictive models for power factor correction in aircraft systems. Dalamagkidis, Valavanis, and Piegl (2009) The choice of machine learning algorithms is critical, with regression algorithms, neural networks, or ensemble methods being employed based on the complexity of the data and the accuracy required. Latorella and Prabhu (2017) Machine learning algorithms can also be employed for fault detection and diagnostics within the power factor correction system, flagging anomalies or deviations from expected performance for proactive maintenance and troubleshooting.

Optimization algorithms for capacitor bank sizing

Natural selection and genetics are the foundation for genetic algorithms (GAs), which use selection, crossover, and mutation to evolve a population of viable solutions. Particle Swarm Optimization (PSO) was developed based on the social behavior of particles in a swarm, where each particle represents a possible solution. Rehman et al., (2022) Ant Colony Optimization (ACO) directs ants toward the best routes by drawing inspiration from their foraging habits. Potential solutions can be represented as routes in ACO algorithms, which can then be modified for capacitor bank size. Zolghadri et al., (2014) A probabilistic optimization technique called "simulated annealing" was motivated by the annealing procedure used in metallurgy accepting poorer answers with diminishing probability, enabling the algorithm to get out of local optima. DE is a population-based optimization technique that evolves a population toward ideal solutions by combining crossover, mutation, and selection procedures.

Optimization algorithms play a crucial role in capacitor bank sizing, offering benefits such as global optimum search, dynamic adaptability to changing electrical load conditions, efficient energy utilization, and reduced computational burden. Shaikh et al., (2019) They can explore the entire solution space, ensuring the capacitor bank configuration is a global optimum and can dynamically adapt to changing electrical load conditions.

Previous research in aviation power factor correction

Power factor correction in aviation systems has been the subject of several books and academic studies. Linares, Exposito, and Vasic (2023) found that compact form-factor converters drive the need for highly efficient high-frequency magnetic components. This study focuses on enumerating the rules for designing asymmetric three-phase magnetic components.

Recent research has demonstrated multi-phase energy systems' advantage over three-phase energy systems, particularly in power production, transmission, distribution, and usage. These benefits include reduced total harmonic distortion (THD), affordability, efficacy, and dependability. Since multi-phase transformers require a multi-phase signal that is pure sine wave in nature, they are necessary for evaluating the characteristics of a multi-phase motor. This study aims to assess several static multi-phase transformation methods and explore multi-phase power transformation from a three-phase system. The Tabrez et al., 2021

An enhanced single-ended primary inductance converter (SEPIC) with BLDC motor driving is suggested by this study. An ant-lion optimizer (ALO) approach is used to analyze the control architecture of a fractional order proportional-integral-derivative (FOPID) controller in the updated SEPIC converter developed with a switched inductor. The utilization of BLDCM in the upgraded control topology of SEPIC is employed to address power factor correction and PQ problems. Sivakumari, Karthika, and Renuga (2020)

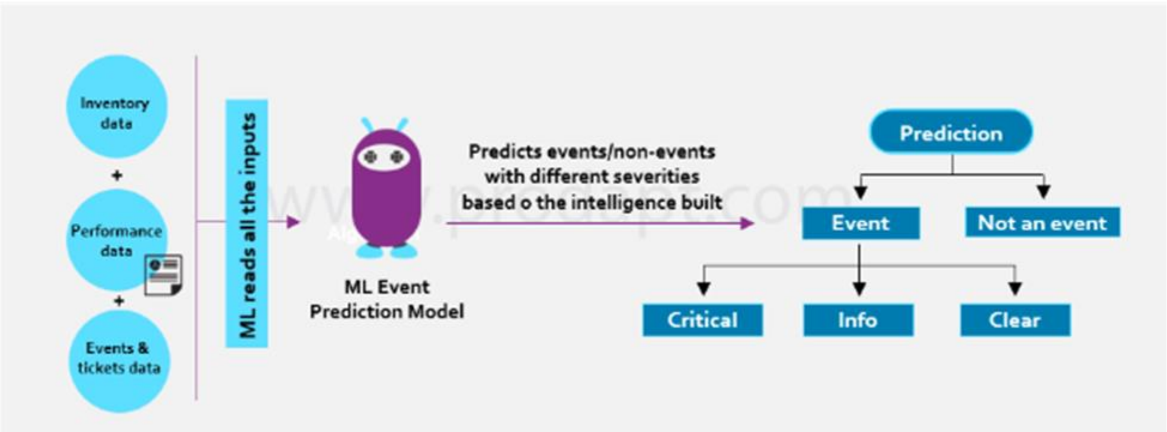
III. METHODOLOGY

Data collection and real-time monitoring in aviation systems

The research uses various data sources within aircraft systems, including onboard sensors, avionics, and monitoring devices that capture electrical parameters like voltage, current, and power factor. Real-time data acquisition uses high-frequency systems to capture electrical data from various aircraft components.The research aims to enhance the adaptability and intelligence of the power factor correction process in aviation, contributing to improved energy efficiency and sustainability in aircraft operations.

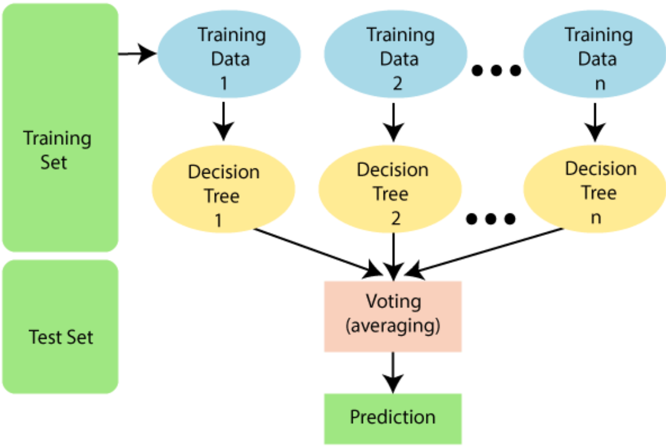
Machine learning techniques for predictive modeling

Figure 1: Using operational data to apply an event prediction model Goel, Goel, and Kumar, (2023)



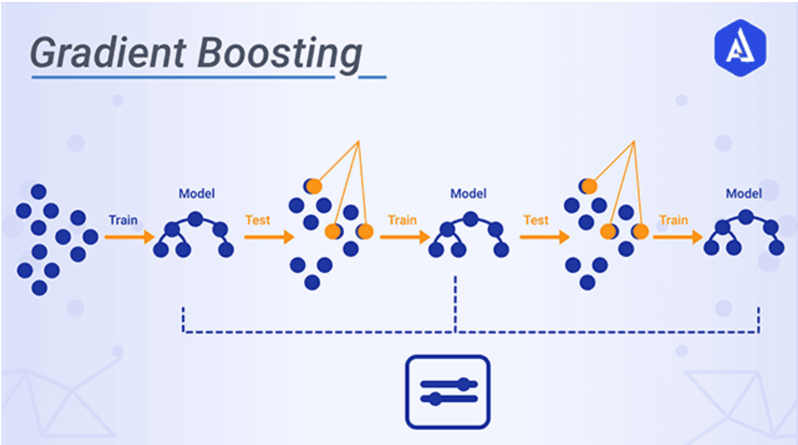
Using network node performance data, an event prediction model forecasts the occurrence and severity of a network event in advance.

Figure 2. Forest Classifier at Random Huo et al., (2021)



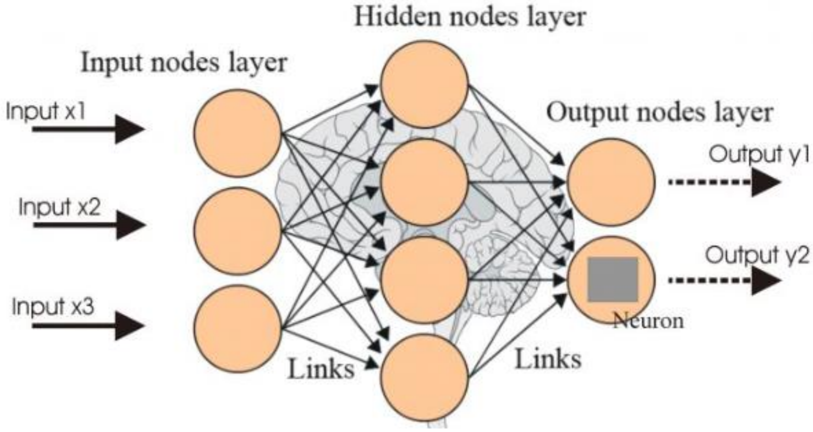
The most used method for classification problems is random forest. It can make accurate predictions with fewer high-quality data points and is simple to train given the necessary inputs.

Figure 3. Boosting Classifier using Gradient Rodriguez-Galiano et al., (2015)



Compared to the random forest classifier model, it is more sophisticated. The prediction accuracy is mostly higher and can be easily trained to yield optimal outcomes.

Figure 4. Neural Systems Balasubramanian et al., (2021)



Larger VMs or GPUs for training, more RAM, and more adjustments from SMEs are needed for this. Scalability for more enormous datasets is present.

Optimization algorithms for capacitor bank size and placement

This section briefly explains the optimization techniques employed in the study, namely the Salp Swarm Optimization method. Following that, their solutions for the suggested optimization models are provided.

Dragonfly Algorithm

Dragonflies are a source of inspiration for DA. Consequently, a random population of n dragonflies, each representing a variable, populates the search space. The following equation determines how the locations of the dragonflies are changed with each algorithm iteration.

$\Delta Xt+1=(sSi+aAi+cCi+fFi+eEi)+w\Delta Xt$ (1)

Where s, a, c, and w are the weights of separation, alignment, cohesion, and inertia, respectively. The two additional coefficients, f, and e, respectively, stand in for the food component, and the adversary factor approach takes into account the individual by distinguishing The terms Si, Ai, Ci, and Ei represent the independence, alignment, and cohesiveness, food supply, and opponent location, respectively. Each iteration updates each of these parameters [27]. The separation is computed using the given formula.

$Si=-\sum j=1NX-Xj$ (2)

where $X-Xj$ is the separation between the present person and people nearby. Keep in mind that N represents the number of neighbors.

Likewise, alignment is just the same as:

$Ai=\sum Nj=1VjN$ (3)

Where Vj represents the relevant individual's velocity, this is how the concept of cohesiveness is illustrated.

$Ci=\sum Nj=1XjN-X$ (4)

The two most crucial actions are avoiding adversaries and being drawn to a food source. In terms of math, they are equal to $Fi=X+-X$ (5)

$Ei=X—X$ (6)

Where X denotes the enemy's position− and the food by $X+$, the revised position vectors can be found in the manner described below.

The Salp Swarm Optimization method

Salp Swarm Optimization models the swarming behavior of salps. There is a leader salp at the beginning of a salp chain, and follower salps along the chain. As a result, the populace is divided into two groups: followers and leaders. The leader Salp's solution updates are represented mathematically as follows: (1)

$x1j=\ \{Fj+c1((ubj-lbj)c2+lbj)\ c3\geq 0$

$\quad Fj-c1((ubj-lbj)c2+lbj)\ c3<0\}$ (7)

Where, in the jth dimension, $x1j$, Fj, ubj, and lbj stand for the upper bound, lower bound, food supply position, and leader salp position, in that order. In the [0,1] interval, the other variables, $c1$, $c2$, and $c3$, are all random integers. Equation (8), which displays the exploration and exploitation behavior, is balanced by the algorithm's parameter $c1$.

$c1=2e-(4l/L)2$ (8)

L and l, in turn, provide the maximum and current iteration counts.

Additionally, the followers adjust their placements. The updates for follower salps are displayed in equation (9), where j is the jth dimension and xij is the ith salp location—information on the followers' motion calculation.

$xij=12xij+xi-1j$ (9)

Following position updates, the halting situation is examined. If not, assessing the objective function values is the first step in the process.

Testing System and Preparing Data

Figure 5. Aviation single-line schematic for a 17-bus radial distribution network

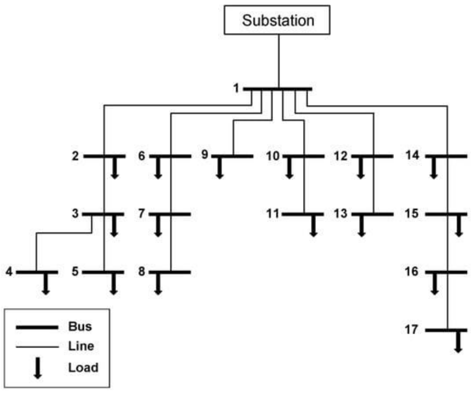
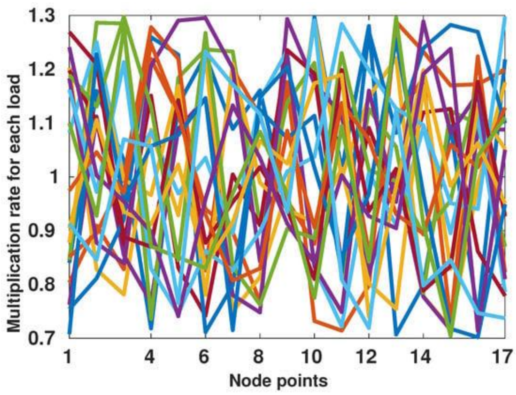


Figure 6. A random sample of twenty multiplication rates was used for every base caseload.



Assuming that the 17-node component is a radially topologically balanced system, as shown in Figure 5, we created 1000 distinct random load profiles to simulate variations in the load profile across different time intervals, such as changes over a day or days. An example of 20 randomly generated branch reactance multiplication rates per node is shown in Figure 6.

Simulation Outcomes

We solved the suggested optimization models using the SSA and DA toolboxes in Matlab, a simulation program.

Case 1: Set Sizes for Capacitors

We employed five capacitors to solve the first optimization model, whose lowest and most extraordinary capacities ranged from 25 to 400 kvar. We employed 30 search agents and a 500 iteration limit for each simulation. In the first set of simulations, the optimum sizing and placement problem is assumed to be fixed for capacitor sizes.

Table 1. The simulation results with SSA and DA for Case 1 are the best and worst

Method	Locations					Sizes (kvar)					F
DA (b)	5	14	15	16	17	400	400	400	400	400	324,917.31
DA (w)	7	14	15	16	17	267.12	289.74	376.83	343.84	400	336,775.59
SSA (b)	5	14	15	16	17	400	400	400	400	400	324,917.31
SSA(w)	11	14	15	16	17	74.38	109.19	400	400	400	338,625.19

The best and worst near-optimal solutions found with DA and SSA are displayed in Table 1. The best outcomes were exhibited by DA(b) and SSA(b), respectively, whereas DA(w) and SSA(w), which represented DA and SSA from 100 separate runs, showed the lowest results.

Figure 7. System voltage levels both before and following capacitor installations in different stress conditions

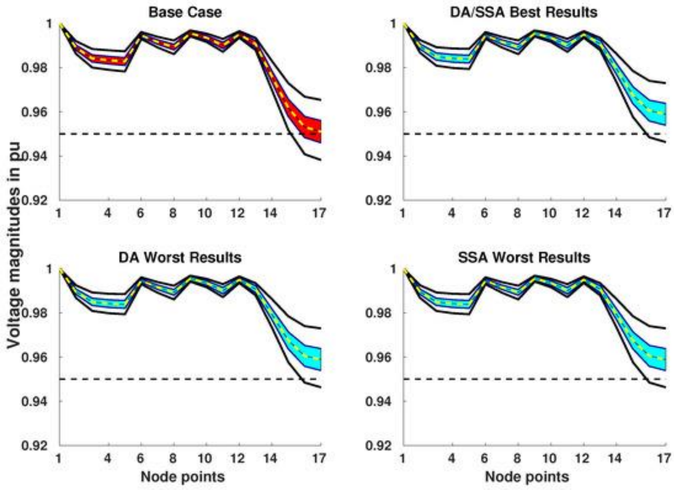


Figure 8. A simple example of Model 1 displays the DA and SSA standard deviations and mean voltage magnitudes

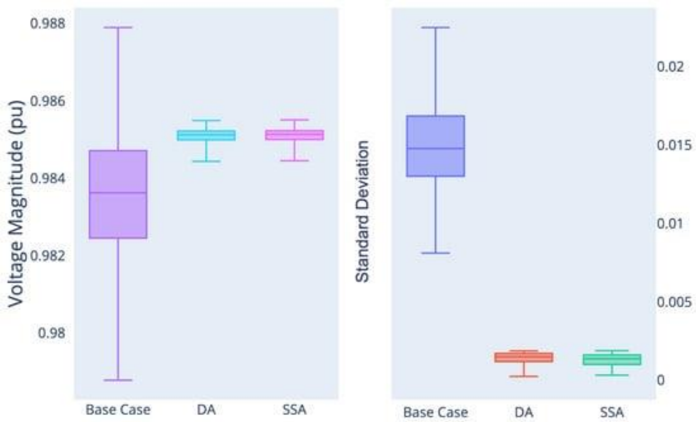
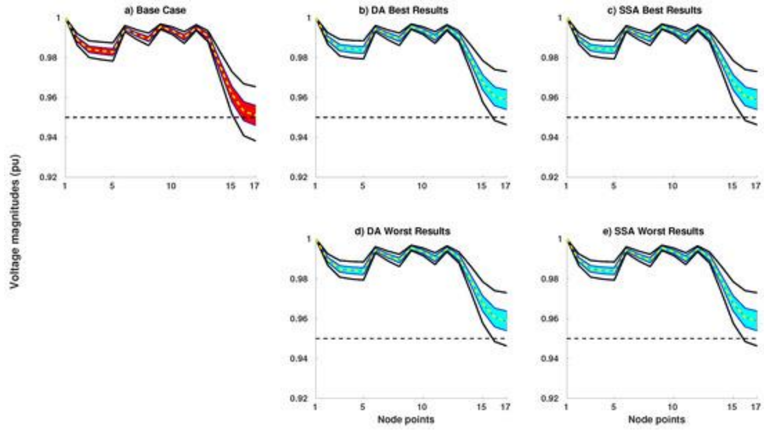


Figure 7 shows the mean of the base case voltage magnitudes and their standard deviations, with the first component being emphasized in red. The voltage magnitudes from the best DA/SSA runs (those with the lowest objective function values) and the worst DA/SSA runs are shown in the following sections.

Case 2: Changing Tap Positions to Provide Variable Capacitor Sizes

We produced 1000 distinct load profiles in the simulations by varying the loads, much like in Case 1. Unlike instance 1, this instance establishes the capacitance tap placements, sizes, positions, and modes of operation under diverse load circumstances.

Figure 9. Voltage levels following capacitor installations, the findings are displayed as the base case, best near-optimal using DA, best near-optimal using SSA, very near-optimal when utilizing DA, and extremely near-optimal when utilizing SSA



The voltage magnitudes for the baseline scenario and the top and bottom outcomes following 100 iterations of DA- and SSA-based techniques are displayed in Figure 13. As the illustration illustrates, optimizing the capacitors' size, location, and operating characteristics with the use of heuristic optimization techniques might lead to an improved voltage profile in extremely uncommon circumstances (such as higher loads at the laterals' terminal nodes), similar to instance 1; this instance could nevertheless contain a few under-voltages.

IV. DISCUSSION

Limitations and areas for further research

The study uses SSA and DA algorithms to optimize capacitor sizes and placements in Case 1. Al-Rubaye, Tsourdos, and Namuduri (2023) The results show that both techniques yield similar optimal positions and heights for near-optimal solutions, while for worst-case solutions, capacitor placements and sizes vary between SSA and DA. In case 2, capacitor values under various load scenarios were explored using SSA and DA. Larger capacitor values with minimal variations indicated more effective outcomes. Voltage profiles significantly improved with optimal sizing, placement, and operation of capacitors using SSA and DA. Active power losses decreased noticeably when capacitors were optimally sized and located. SSA yielded slightly lower functional power loss values than DA in the optimal configuration. Flin, O'Connor, and Mearns (2002) demonstrate that strategic placement and sizing of capacitors effectively improve voltage profiles and reduce power losses in aviation systems.

V. CONCLUSION

The research aimed to identify and analyze power quality challenges in complex aircraft electrical loads, including voltage sags, phase imbalance, and power factor issues. The study focused on power factor correction to mitigate these challenges and prevent adverse effects on the lifespan of electrical equipment and overall system performance. Both SSA and DA were employed for optimizing capacitor sizes and placements. Voltage profiles improved in all simulations, even in worst-case scenarios for SSA and DA. Capacitor additions led to reduced standard deviations from mean voltage magnitudes.

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