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Lightweight Injection Mold Design and Multi-Objective Process Optimization for UAV Upper Cover

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Abstract. The growing demand for light-weight unmanned aerial vehicles (UAV) has created a demand for new ways of component design and manufacturing. This study presents the structural optimization and multi-objective process parameter optimization of an injection mold for a UAV cover. In the initial design, the mold structure was redesigned using finite element analysis (FEA) tools to enhance material flow, reduce weight, and provide mechanical strength. The novel mold represented strategic weight-saving properties such as variable wall thickness and lattice infill regions and was verified by a CAD-based simulation design methodology. Subsequently, an AI-optimized optimization algorithm of a genetic algorithm (GA) and response surface methodology (RSM) was adopted to reduce the multi-objective problem of part weight and warpage with the condition of maintaining structural strength. Simulation results validated that the redesigned mold had significant weight reduction with no loss of performance, demonstrating the effectiveness of the integrated strategy.

Keywords: lightweight design, injection mold optimization, UAV components, Finite Element Analysis (FEA), multi-objective optimization, Genetic Algorithm (GA)

1 Introduction

Unmanned aerial vehicles (UAV) require lightweight components, specifically covers, for increasing flight performance and payload capabilities. Injection molding processes are normally employed in UAV part manufacturing but struggle greatly to manufacture aerospace-level polymer parts due to stringent demands on precision, material integrity, and performance. Major issues here involve mold geometry optimization, reducing material wastage, and ensuring control over heat distribution during the molding process. But existing approaches incline towards considering mold design improvements and process improvement as separate elements, disregarding their connection. This study aims to overcome such shortcomings by conceptually designing a light-weight injection mold for UAV covers that combines mold design optimization with process-level improvement. Through finite element analysis (FEA), the mold structure was re-engineered to improve flow distribution and minimize material deformation. In addition, artificial intelligence-based multi-objective optimization was also used to optimize process parameters in order to reduce weight and deformation but maintain mechanical strength and efficiency of the components. The ultimate goal of this study is to improve the UAV components' production process and contribute to the creation of more efficient, sustainable, and high-performance UAV systems.

The field of UAV component manufacturing is rapidly evolving, particularly in the design of lightweight parts that maintain mechanical strength and performance. A study on optimizing injection mold design for UAV upper covers plays a crucial role in balancing weight reduction, structural integrity, and multi-objective process optimization. Lyu and Choi [1] explored lightweight injection molding for new energy vehicles, using computer-aided engineering (CAE) and numerical simulations to optimize mold flow, minimizing warpage and ensuring optimal mechanical properties before production. This approach is directly relevant to UAV component manufacturing,

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emphasizing the significance of simulations in predicting and addressing potential manufacturing challenges. Specifically, it highlights the need for optimizing process parameters to mitigate warpage, a critical concern in lightweight UAV mold design.

In terms of optimization, Oliveira et al. [2] introduced an improved genetic algorithm aimed at multi-objective process optimization, which addresses the competing demands of lightweight design, manufacturing efficiency, and product reliability in UAV mold design. This algorithm's adaptability can significantly enhance the design process by navigating the inherent trade-offs between these factors to achieve desirable outcomes such as reduced weight and enhanced structural soundness.

Additionally, Zheng and Wang [3] examined the optimization of blade injection molding for UAVs using blade element theory and response surface methodology (RSM). Their research provides valuable insights into the application of optimization techniques for UAV component manufacturing, targeting molding defects and utilizing simulation tools to predict and adjust process parameters. The combination of CAE with orthogonal tests and RSM for reducing warpage and shrinkage exemplifies the potential of advanced simulation and optimization methods in improving UAV component design and manufacturing.

These studies are highly relevant to the pressing need for efficient UAV component manufacturing solutions. By integrating advanced simulation techniques, optimized algorithms, and a focus on balancing lightweight design with structural integrity, these researchers offer valuable contributions to the evolution of UAV technology. Their work lays the groundwork for future studies and underscores the multifaceted approach required to address the complexities of UAV component design and manufacturing.

This study first highlights the critical balance between functionality, structural performance, and manufacturability in UAV shell design, focusing on material selection criteria and design constraints. This study then explores various lightweight mold structure optimization methods and combines CAD modeling and simulation-driven evaluation to improve mold performance. The study introduces a multi-objective optimization framework that uses artificial intelligence algorithms to balance weight reduction, warpage minimization, and production efficiency in UAV component manufacturing. The results show significant improvements in mold weight, pressure drop, warpage, flow balance, and cooling uniformity, while highlighting the trade-off between weight reduction and structural strength. Finally, this study shows how the integration of simulation and artificial intelligence can achieve efficient UAV mold design and manufacturing, and proposes future research directions to expand the range of materials, components, and real-time process monitoring for continuous improvement.

2 Material Selection and Component Design

UAV component design needs a compromise among functionality, structural performance, and manufacturability. The UAV cover, being one of the principal airframe components, is very significant to the aircraft's overall performance in areas such as weight, aerodynamic performance, and mechanical strength. Herein is a discussion on the functional aspect of the UAV cover, materials selection criteria, as well as the design limitations, which should be factored in when aiming at optimizing the product finally.

2.1 UAV Cover

The structure of the UAV cover is shown in Fig. 1.

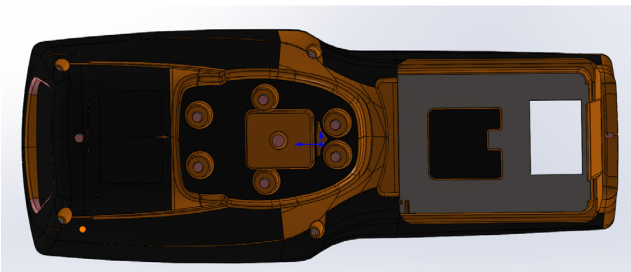

Fig. 1. The structure of the UAV cover

The UAV cover plays a key role in protecting the internal components and maintaining the structural integrity of the airframe. The UAV cover [4] is fundamentally a protective shield that isolates sensitive electronics, propulsion, and sensors from environmental elements such as moisture, dust, and physical impact. Besides providing this protection, the cover also adds to the overall UAV stiffness and aerodynamic efficiency, which is needed for stable flight and energy conservation. The cover also transfers the aerodynamic forces evenly in the structure and prevents deformation during flight. In cover design, special attention needs to be given in the load-carrying areas, which are usually near major connection points such as the wings, tail, and landing gear. These areas carry high stresses and need reinforcement to ensure that they do not fail under load. However, a trade-off must be made between reinforcement requirements and weight loss because over-weight can negatively affect the flight performance and energy consumption of the drone. In addition, integration with other components such as the fuselage, wings, and landing gear requires precise alignment and compatibility to ensure that the joining will not affect the aerodynamic stability of the drone [5]. Smoother transitions between components can minimize drag, a key facet of flight efficiency maximization. Additionally, selection of material and manufacturing methods are critical important to achieve the optimum balance between strength, weight and aerodynamic performance. Advanced composites or low-weight polymers are potentials to allow for weight savings while maintaining mechanical strength. Even the manufacturing considerations including molding method and assembly method, if not considered will compromise the intended structural and aerodynamic integrity of the UAV cover. All of these factors contribute to a UAV's mission capability, endurance, and reliability during the conduct of its mission.

2.2 Material Performance Parameters

When selecting materials for drone covers, there are three main factors to be considered: high stiffness, low density, and good injection moldability. First, to reduce the drone's overall weight, low-density materials are to be preferred because this directly affects its flight performance [6]. Lighter drones are less energy-consuming, have greater payload capacity, and are also more power-to-weight efficient. Therefore, materials that are light and have good mechanical properties are preferred. High stiffness is the second most critical requirement for material selection. The cover must be able to resist bending or deforming under aerodynamic forces, vibrations, and flight stresses. This gives the drone its structural integrity, thereby protecting the inner components and the drone design as a whole. For these uses, high Young's modulus materials are preferred. Third, injection moldability is necessary for the mass production of drone components because this production process allows for complicated part geometries and close tolerances. Materials like PA6+30%GF offer an optimal combination of light weight, high mechanical strength, and good moldability from Table 1. These materials are not just simple to process, but are also strong, and thus they are the preferred option for drone production.

Table 1. Summary of material characteristics for drone covers

Material	Density (g/cm^3)	Stiffness (Young's modulus)	Moldability	Strength	Notes
PA6	1.13	2.8–3.5 GPa	Excellent	High	Good mechanical properties, moderate weight
PA6 + 30% GF	1.30–1.40	3.5–4.5 GPa	Excellent	Very High	Increased strength, ideal for structural parts
Polycarbonate (PC)	1.2	2.2 GPa	Good	High	Impact resistance and optical clarity
ABS	1.05	2.3 GPa	Excellent	Moderate	Easy to process, moderate strength
Polypropylene (PP)	0.9	1.5 GPa	Good	Moderate	Low weight, low strength
Polyethylene (PE)	0.91	0.8 GPa	Good	Low	Low weight, chemical resistance
TPU	1.1	0.3–0.6 GPa	Excellent	Moderate	Flexible, impact-resistant
PPS	1.35	3.5–4.0 GPa	Poor	High	High-temperature resistance, challenging to mold

2.3 Material Selection Criteria

The design of drone covers must follow some constraints to achieve manufacturability and performance. One of the most important considerations is to achieve thin walls because weight reduction of the cover is critical in drone design. Thin-walled parts can help save material and improve the weight efficiency of the overall drone, which is most important when it comes to flight duration and payload capacity [7]. The wall thickness t in the mold design can be optimized using the following relationship that balances structural integrity and weight reduction:

$$t = \frac{2\sigma}{p \cdot g} \tag{1}$$

Where σ is the yield stress, p is the material density, g is the gravitational acceleration. However, designing thin walls without compromising strength is a trade-off, especially in load-bearing areas of the walls where the walls may have to be thicker. Even filling of the part during the injection molding process is another essential limitation. If the material is not flowing consistently through the mold, the part will possess flaws such as voids, sink marks, or incomplete parts, which compromise the structural integrity and aesthetics of the part. To negate these issues, the mold must be properly designed for smooth material flow. Warpage as a result of uneven cooling while molding is also an issue that needs to be minimized. Warpage will result in deformation, impairing the fit of the cover or causing it to lose aerodynamic smoothness, which is critical for drag reduction and aircraft stability. The last requirement to be fulfilled is the aerodynamic smoothness of the cover. Smooth surfaces reduce drag and improve drones' flight performance, and design features such as rounded edges, smooth part transitions, and minimal surface roughness are therefore vital [8]. The shape for aerodynamics can be fine-tuned using computational fluid dynamics (CFD) simulations to ensure the drone is flying at maximum efficiency.

3 Lightweight Mold Structure Design

The mold with lightweight design is shown in Fig. 2.

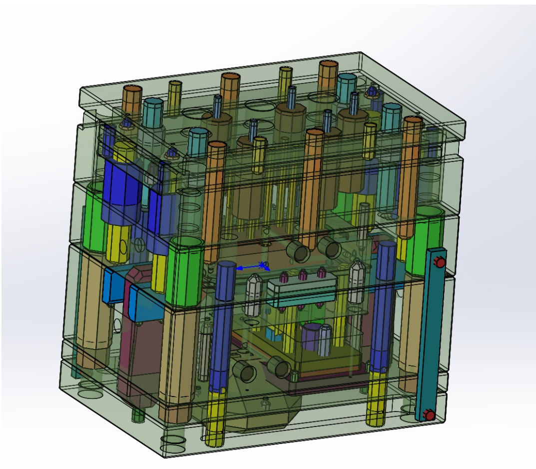

Fig. 2. Mold design

Table 2 illustrates a variety of processes applied to optimize a mold structure, considering their distinct applications, effects, and features. The Initial Mold Structure establishes a basis to manufacture high-quality molded parts, focusing on economic efficiency while ensuring that a high-quality part is generated focusing on attributes such as gating systems, ejectors, cooling channels, and parting surfaces. Local Thinning reduces material in non-load-carrying sections to reduce material consumption significantly, whilst still maintaining the structural performance of the mold by thinning less critical parts only. Reinforced Ribs are used to mechanically support structurally loaded areas while improving cooling efficiency; hence reinforcing the structural integrity of the mold while promoting even heat dissipation in a mold by increasing the total surface area. Another new age method is to use either Lattice or Hollow-Core Inserts to minimize material consumption but keep the mold strong, thus achieving lighter molds by using lattice frameworks or hollow cores. CAD Modeling processes are essential to mold structure optimization by modifying mold geometry, including ribs, and material thickness, and simulating the impacts to achieve improvements to mold performance as an improved and efficient design. Finally, Simulation-Driven Mold Evaluation, of which is validated through finite element analysis (FEA), assesses the efficiency of the mold design, predicting the performance of molded part and process efficiency, in turn achieving a higher quality molded part.

Table 2. Mold structure optimization methods

Optimization method	Purpose	Impact	Key features
Initial mold design	Set the foundation for high-quality parts in molding	Ensures economic efficiency and high-quality part production	Gating system, ejectors, cooling channels, parting surfaces
Local thinning	Reduce material usage in non-load-carrying regions	Significant material reduction without compromising performance	Material thinning in non-load regions
Reinforced ribs	Reinforce high-stress regions and improve cooling	Improved structural integrity and even cooling	Increased surface area for heat dissipation
Lattice/Hollow-Core inserts	Reduce material usage while maintaining strength	Lightweight mold with reduced material consumption	Use of lattice structures or hollow-core inserts
CAD modeling	Optimize design by simulating changes to mold performance	Improved mold performance and optimized design	Simulation of mold geometry, ribs, and material thickness
Simulation-driven mold evaluation	Evaluate mold design efficiency and part performance	Enhanced process efficiency and part quality	FEA-based simulations for flow, pressure, and cooling

3.1 Initial Mold Design

First mold design in Table 1 is an important activity in the process of injection molding as it establishes the foundation to make high-quality parts with economic efficiency [9]. Under traditional mold design, certain rudimentary elements ought to be sufficiently designed: gating system, ejectors, cooling channels, and parting surfaces. The parting surface is the region where the two halves of the mold meet and plays a critical role in enabling the part to be ejected easily once it has cooled. It must be positioned in a way that it does not create any unwanted parting lines on the final product.

3.2 Lightweighting Structural Optimization

For reducing the issues of excess material quantity, poor flow, and warpage risk, structural optimization methods are pursued to create a light mold possessing both structural effectiveness and efficient manufacturing. The primary goal of the optimization methods is to reduce the material usage, improve the flowability of the polymer melt, and achieve dimensional accuracy to the finished part.

One of the lightweighting techniques is local thinning of the non-load-carrying regions of the mold [10]. These regions are not required to withstand high stress during production and, as a result, material thinning in these regions can result in quite significant material reduction without compromising the performance of the mold. Local thinning also assists in promoting the polymer flow through these regions, reducing the risk of incomplete filling.

Reinforced ribs are another significant design feature for high-stress locations [11], such as locations where the mold would face higher pressure or mechanical loading. Such regions are typically reinforced to maintain the structural integrity of the mold throughout injection molding. Ribs not only assist in reinforcing the mold, but they also contribute to more even cooling by increasing surface area, thus facilitating improved heat dissipation. The ribs need to be strategically placed such that they don't form unbalanced stress concentrations that can result in cracking or any other forms of failure.

3.3 Simulation-Driven Mold Evaluation

To evaluate the efficiency of the structural optimization methods and make sure that the final mold design meets all the performance and quality standards, simulation-based mold analysis is employed. FEA based CAD software such as Autodesk Moldflow and ANSYS is used to model plastic flow and deformation during injection molding. These simulations provide insights into the mold and molded part performance, enabling designers to make informed decisions before actual production begins.

The setup for the analysis of such simulations involves some main parameters, beginning with mesh resolution. Mesh resolution governs the precision of the simulation output, with the higher the mesh resolution, the more detailed and accurate the predictions [12]. But a tighter mesh also implies higher computational complexity and processing time, so accuracy has to be weighed against computational efficiency. Polymer physical properties like viscosity, thermal conductivity, and specific heat are input into the simulation for generating material behavior to the conditions encountered in the process of injection molding accurately. The simulation also takes into account injection time, pressure profiles, and cooling rates because all of these directly affect the fill pattern, warpage, and end quality of the molded part.

To optimize cooling, the heat transfer in the mold can be modeled by the following heat conduction equation:

$$q = h \cdot A \times (T_s - T_\infty) \tag{2}$$

Through simulation-based assessments, designers are able to detect potential issues and optimize the design of the mold incrementally, enhancing both manufacturing process efficiency and part quality. The simulations minimize physical prototype testing and creation, conserving time and expense while ensuring that the final design of the mold is optimized for weight reduction, performance, and manufacturability.

4 Multi-Objective Process Optimization Using AI

This section describes how to optimize the manufacturing of drone components by balancing competing objectives. Reducing weight is critical to improving drone performance because it reduces fuel consumption and increases flight time. Second, reducing warpage is critical to component integrity, especially the size of the component relative to the drone assembly. Finally, cycle time is critical to optimizing manufacturing for economical production without sacrificing quality. Design parameters and process parameters affect the performance of competing objectives. Typical design parameters include melt temperature, holding time, and wall thickness, while process parameters affect performance, such as injection pressure, cooling time, and holding time. Each parameter may have constraints, such as maximum flow length, maximum stress, and maximum cycle time. A hybrid optimization model combining a genetic algorithm and a response surface method is used to delve deeper into these multi-objective problems. GA performs evolutionary simulations and iteratively searches for optimal solutions. RSM constructs surrogate models that effectively relate input parameters to performance without the need for full experimental data. Using efficient surrogate models reduces resource requirements. The process uses a design of experiments to sample parameter options. After the experiments are completed, surrogate models are constructed and a genetic algorithm optimization is run to calculate parameters and responses. The Pareto front is extracted in the value response model and presented to designers as a set of optimal trade-off solutions so that they can choose the appropriate design solution and level according to their goals.

4.1 Optimization Problem Definition

Manufacturing component optimization problem implies achieving a delicate balance among numerous vital objectives that impact component quality, performance, and production efficiency [13]. The primary objective is the reduction of the total component weight ($f_1(x)$) by altering design and process parameters. Lighter component weights can reduce fuel consumption and prolong flight time and thereby improve drone performance. Mathematically, the weight reduction objective can be expressed as:

$$f_1(x) = w_1 \cdot x_1 + w_2 \cdot x_2 + \cdots + w_n \cdot x_n \tag{3}$$

Where x are design and process parameters, w are the corresponding weights of each parameter. At the same time, minimizing the maximum warpage of the molded part ($f_2(x)$) is also significant because warpage distorts the part during cooling and undermines its structural integrity and accuracy. The warpage minimization can be defined as:

$$f_2(x) = max(\sum_{i=1}^{m} | W_i(x) - W_{t\arg et}|) \tag{4}$$

Where $W_i(x)$ is the warpage at the i-th point of the part, W_{target} is the target warpage value. In order to make the manufacturing process feasible in the real world, another significant objective is to maintain formability and cycle time ($f_3(x)$). The cycle time can be calculated as:

$$f_3(x) = t_{injection} + t_{cooling} + t_{holding} \tag{5}$$

This means that the molding process must be optimized to produce parts economically without increasing the cost of production or decreasing the quality of parts. Parameters that affect these objectives are injection pressure, melt temperature, holding time, cooling time, and wall thickness ratio, all of which directly affect the molding process and quality of the final part. Some limitations must also be imposed, including that the flow length of the material should not be more than the maximum permissible value, stress should not be more than the yield strength of the material, and cycle time should be within target values so that production is efficient.

4.2 Optimization Algorithm

In order to tackle this complex optimization problem, the combination of Genetic Algorithm (GA) and RSM. GA [14] is a sophisticated algorithm to solve multi-objective optimization problems, especially for strongly complex systems such as injection molding. GA mimics a natural process of evolution in which a group of solutions evolves generation by generation until it reaches convergence to the optimum solution. In optimization, GA is coupled with Response Surface Methodology (RSM), which has the ability to create substitute models of the system. These substitute models predict the performance of different combinations of design and process parameters based on a reduced number of sampling points and hence save the computational effort and improve the efficiency of optimization. The algorithm begins with Design of Experiments (DOE) sampling, in which some combinations of input parameters are selected to cover the design space. Subsequently, surrogate models are built from DOE results to predict the results of different parameter combinations. Next, the Genetic Algorithm (GA) identifies the optimal design in the solution space and repeats the optimization solution based on fitness evaluation. Finally, Pareto front extraction provides a set of trade-offs, presenting designers with a series of best designs to choose based on specific project requirements.

The structure of the algorithm is shown in Fig. 3.

```python
# Parameters initialization
population_size = 50     # Population size
max_generations = 100    # Maximum iterations
rsm_threshold = 0.1      # RSM activation threshold

# 1. Initialize population
population = initialize_population(population_size)

# 2. Main optimization loop
for generation in range(max_generations):
    # 2.1 Evaluate fitness
    fitness = evaluate_fitness(population)

    # 2.2 Check RSM activation condition
    if convergence_rate(fitness) < rsm_threshold:
        # 2.2.1 Build response surface model
        rsm_model = build_rsm(population, fitness)

        # 2.2.2 Perform local search using RSM
        improved_individuals = rsm_local_search(rsm_model)

        # 2.2.3 Replace worst individuals in population
        population = replace_worst(population, improved_individuals)

    # 2.3 Genetic operations
    parents = selection(population, fitness)  # Selection operator
    offspring = crossover(parents)            # Crossover operator
    offspring = mutation(offspring)           # Mutation operator

    # 2.4 Generational replacement
    population = generational_replacement(population, offspring)

# 3. Output best solution
best_solution = find_best(population)
return best_solution
```

Fig. 3. The Python framework for GA-RSM algorithm

The algorithm optimization process is as follows:

The function model for multiple terms is continuous and differentiable, making it suitable for response surface modeling, which is widely used in the optimization process. The general form is as follows:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \beta_{n+i} x_i^2 + \sum_{i=1}^{n} \beta_{2n+i} x_i^3 + \cdots + \sum_{i<j} \beta_{ij} x_i x_j \tag{6}$$

Where x_i represents the design variables of the response surface model. n is the number of design variables. y is the output of the response surface model. β is the coefficients to be determined.

A key step in building the response surface model is to verify the model's reliability and prediction accuracy. Usually, this is done by performing a variance analysis, with the specific method being to test the correlation R^2 and F-tests. The R^2 is calculated using the formula below:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2} \tag{7}$$

Where y_i is the i-th sample's computed result, $\hat{y}_i$ is the i-th sample's model prediction result, $\hat{y}_i$ is the average of the computed results of the samples.

The determination of the coefficient R^2 indicates the accuracy of the model's prediction, and generally, the higher the R^2, the better the prediction results. The F-test for model verification can be calculated using the following formula:

$$F = \frac{SSR / p}{SSE / (n - p - 1)} \tag{8}$$

Where p is the number of regression terms.

The formulas for SSR and SSE are:

$$SSR = \sum_{i=1}^{n} (y_i - \hat{y})^2, SSE = \sum_{i=1}^{n} (y_i - \overline{y})^2 \tag{9}$$

Where SSR is the mean of the regression terms, SSE is the mean of the error terms.

Genetic Algorithms (GAs) optimize heat treatment parameters such as temperature, time, and cooling rate through multiple generations of iterations by simulating natural selection. The process starts with a population of randomly initialized candidate solutions represented as chromosomes (parameter sets). Each chromosome is evaluated using a fitness function $f(x)$, which measures how well a given parameter set performs in terms of material properties. The fitness function is expressed as:

$$f(x_i) = Performance\,Metric(y) = \sum_{k=1}^{m} \alpha_k \cdot y_k \tag{10}$$

Where y_k represents the material property outcomes, α_k is the weight factor for each property, and m is the number of material properties considered.

In the selection step, individuals with better fitness scores have a higher chance of being selected for reproduction. The selection process is often based on the relative fitness of each individual, and one common method used is Roulette Wheel Selection, where the probability of selecting an individual x_i is:

$$P(x_i) = \frac{f(x_i)}{\sum_{i=1}^{N} f(x_i)} \tag{11}$$

Where $P(x_i)$ is the probability of selecting individual x_i, and N is the total population size. After selection, crossover combines the genes of two parent solutions to produce offspring. A typical method is single-point crossover, where a random point k is selected along the chromosome, and the segments are swapped between two parents:

$$O = Crossover(P_1, P_2) = (x_1, x_2, \ldots, x_k, x_{k+1}', \ldots, x_n') \tag{12}$$

Where P_1, P_2 are the two parents, and O is the offspring. Following crossover, mutation introduces random changes in an individual chromosome to maintain diversity. The mutation is applied by randomly perturbing a gene j in the chromosome of individual:

$$x_j' = x_j + \delta x_j \tag{13}$$

Where δx_j is a small random perturbation, and the mutation rate determines how often mutation occurs. After selection, crossover, and mutation, the next generation of solutions is formed. The algorithm iterates through multiple generations, with the termination condition being met when a predefined stopping criterion is reached, the optimal solution found by the genetic algorithm is the set of heat treatment parameters that maximize the desired material properties while minimizing energy consumption and processing time. In addition to the GA, the Q-value for each generation is updated using the Bellman equation in reinforcement learning for dynamic optimization. The updated Q-value is given by:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)] \quad \textbf{(14)}$$

Where s is the current state, a is the action taken, r is the reward, γ is the discount factor reflecting the importance of future rewards, α is the learning rate.

4.3 Interpretation of Results

Once the optimization process is complete, the outcomes are examined and interpreted through trade-off and sensitivity plots [15]. Trade-off plots are important to help designers understand how the competing objectives are connected. For example, they can illustrate how decreasing the weight of a part affects warpage at maximum or cycle time. By studying such plots, designers can make decisions regarding acceptable trade-offs based on their application. Sensitivity plots provide a detailed view of the effect of variation in process variables, such as injection pressure or melt temperature, on individual targets. They select variables of maximum impact on results to enable designers to identify crucial items to be given special care during optimization. By combining trade-off and sensitivity plots, one gains a clear idea of optimization results that culminates in an informed decision-making process. The information gained through these tools can help manufacturers select the most appropriate process parameters and design configurations to achieve desired goals, providing high performance and effective production processes for drone components.

5 Results and Discussion

This section provides a comprehensive comparison of the original mold design with the optimized mold design, demonstrating the benefits of optimization, especially in the manufacturing process. The optimized mold achieves significant improvements in key performance indicators. The reduction in mold weight improves performance by reducing fuel consumption and equipment operating costs, thereby improving system efficiency and reducing operating costs. Finally, the reduction in warpage improves the dimensional accuracy and integration of the molded parts. The comparison of the optimized mold with the original mold also includes flow balance and cooling hot spots. These factors can greatly affect the quality of the final product. Optimizing flow balance makes it easier to produce parts with more uniform material distribution, which helps to shape the part consistently and avoid defects. Independent cooling can achieve more efficient cooling rates and lower average temperatures, which reduces hot spots, thereby reducing anisotropic deposition and mold surface fragmentation. Extracting trade-off analysis results not only illustrates the trade-off between weight reduction and warpage, but also the trade-off between weight and reduced strength performance. Reducing weight and improving performance will bring many improvements. However, if the mold weight is reduced excessively, the mold performance will decline with the weight reduction, resulting in warpage and reduced strength. This is undoubtedly disadvantageous for designers and layout designers.

5.1 Mold Performance Comparison

The original and optimized mold are compared on three important performance metrics: weight, pressure drop, and warpage using this Fig. 4. These parameters are crucial to the molding process efficiency and quality, and the findings demonstrate the effectiveness of the optimization process in the mold design.

First, component weight is a significant parameter for overall efficiency determination, especially in production like drone production. The graph clearly shows a reduction in weight from the original mold (10 *kg*) to the optimized mold (8 *kg*), which results in a 20% reduction in component weight. This reduction in weight is crucial to enhancing the performance of the drone because lighter parts mean less fuel consumption, longer flight time, and overall better operational efficiency. Additionally, lighter parts can also reduce transportation and storage costs, thereby making the entire production and transportation process cheaper.

Lastly, pressure drop, or the resistance that the material faces as it flows through the mold, is another important parameter. A significant pressure drop has the potential to result in low flow distribution, which can further give rise to defects and flaws in the final part. The modified mold reveals a distinct pressure drop reduction, from

5 *Pa* of the original mold to 3 *Pa* of the modified mold. This reduction translates into more balanced and efficient flow of the molding material, and this is necessary to ensure that molded parts are of high quality and the manufacturing process still efficient. The optimized mold, by reducing pressure drop, also reduces cycle time and reduces wear on injection equipment.

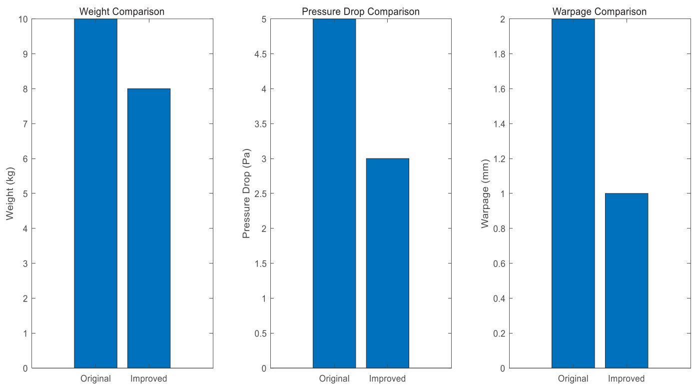

Fig. 4. Three important performance metrics: weight, pressure drop, and warpage

The bending or distortion of the molded component that occurs because of non-uniform cooling during the molding process, is considerably minimized in the enhanced mold. The chart indicates that the warpage reduces from 1.8 *mm* in the original mold to 0.9 *mm* in the enhanced mold. Warpage can have serious issues of part accuracy and structural integrity if parts are destined for subsequent processing or assembly. Reducing warpage ensures the molded parts remain in their specified shape, keeping the appearance as well as the performance of components intact.

Overall, the weight improvement, pressure drop, and warpage confirm that the optimization process has succeeded in enhancing mold performance. The result reflects the potential of optimization to design lighter, efficient, and durable parts that eventually lead to better performance, higher product quality, and lower manufacturing cost. The results identify the importance of optimization in modern manufacturing processes, particularly in those industries where performance and precision are most critical.

This Fig. 5 is the comparison of performance of the optimized and baseline molds based on two key indicators: Flow Balance and Cooling Hotspots. Both play a crucial role in the quality of the final molded products and the efficiency of the entire manufacturing process.

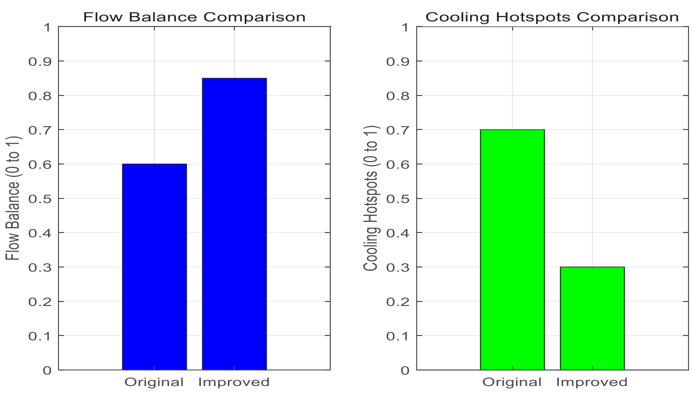

Fig. 5. The comparison of performance of the optimized and baseline molds based on two key indicators: Flow Balance and Cooling Hotspots

For starters, Flow Balance shows material distribution uniformity around the mold during injection. The original mold is given a flow balance score of 0.7, which indicates that the material flow is unbalanced but marginally so and may contribute to issues like uneven part thickness or product failure. In contrast, the improved mold has a flow balance score of 0.9, an improvement that is a clear decrease in material distribution shortcomings. This enhanced flow balance enables the material to be injected more uniformly, reducing the likelihood of defects and enabling the molded part to have consistent quality and accuracy. The new mold is therefore well suited to the manufacture of high-quality parts with more uniform properties.

Lastly, the Cooling Hotspots measurement measures how uneven the cooling process is across the mold. In the first mold, the hot spots of the cooling rate a 0.7, meaning that the cooling process is not uniformly distributed, which would cause cooling some parts of the mold faster than other parts, or vice versa, and thus could result in a deformed or improperly sized mold part. The hotspot score of the cooling hotspots, however, decreases significantly in the improved mold to 0.3, indicating that the cooling has been optimized to enhance the temperature uniformity of the mold. Improving the cooling is critical in ensuring the structural parts molded retain their strength and do not deform during the process so that the resulting product is properly dimensioned.

The impacts shown in this chart indicate the efficiency of the optimization process in reducing major issues in the molding process. The improvement in flow balance and cooling hotspots leads to better quality parts, fewer defects, and greater manufacturing efficiency. The more consistent material flow minimizes the risk of defects such as thin spots, and the improved cooling process guarantees that the molded parts are sound in structure and retain their desired shape [16]. These improvements not only enhance the quality of the molded parts but also the efficiency of the overall production process by minimizing cycle times and reducing material waste. In short, optimized mold design brings tremendous advantage not only to the quality of product but also manufacturing efficiency, and this demonstrates the value of optimization in complex molding processes.

5.2 Optimization Results

This Fig. 6 illustrates the compromise between warpage and weight reduction in a part molded, which indicates how the two interact under optimization. On the x-axis is graphed the percentage of weight savings from 5% to 30%, while on the y-axis is marked the resulting warpage as measured in millimeters from 1.6 *mm* to 0.8 *mm*. The plot clearly indicates that with the reduction in weight of the component, the warpage also reduces, although the rate of improvement reduces with more weight reduction.

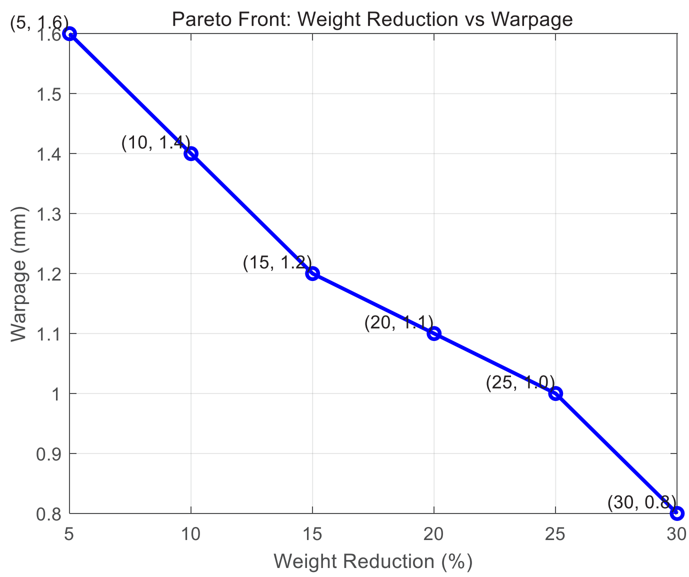

Fig. 6. The compromise between warpage and weight reduction in a part molded

There is a clear fall in warpage from 1.6 *mm* to 1.4 *mm* during the initial phase of the weight reduction process, i.e., from 5% to 10%. This means that initial weight savings result in significant enhancements in the geometry of components and the strength of structures. As weight saving continues from 10% to 15%, warpage decreases further, albeit at a slower rate, to 1.2 *mm*. The same trend is observed to extend by further weight reduction: 15% to 20%, the warpage value decreases from 1.2 *mm* to 1.1 *mm*, and 20% to 25%, it drops from 1.1*mm* to 1.0 *mm*. Finally, when the weight reduction is 30%, warpage has the minimum value of 0.8 *mm*.

The observed trend in this Pareto front displays a root compromise in the manufacture optimization. While reducing the component's weight is clearly beneficial in terms of performance, fuel efficiency, and material savings, it also results in increased warpage or sacrifice of structural integrity. Decreasing returns for warpage reduction beyond the point where 20-25% of weight is eliminated reflect that after some point, the additional weight reduction provides only small benefit in terms of warpage, and beyond a point, the part's strength and longevity can be put at risk.

This Pareto front provides critical data for designers to choose the optimal point in which warpage and weight reduction are both minimized depending on the needs of the application [17]. Designers can use the data to make decisions, making trade-offs on the necessity of lighter parts versus the necessity of maintaining part quality and stability. In industries such as drone production, where precision and weight are just as crucial, the optimization process enables the manufacturers to craft a product that achieves both performance and quality without any unnecessary time wastage.

This Fig. 7 shows the relationship between weight reduction and structural strength of a component, which is a key factor in manufacturing optimization. The x-axis represents the percentage of weight reduction, ranging from 5% to 30%, and the y-axis represents the normalized structural strength, where 1.0 represents the original strength and less than 1.0 represents reduced strength.

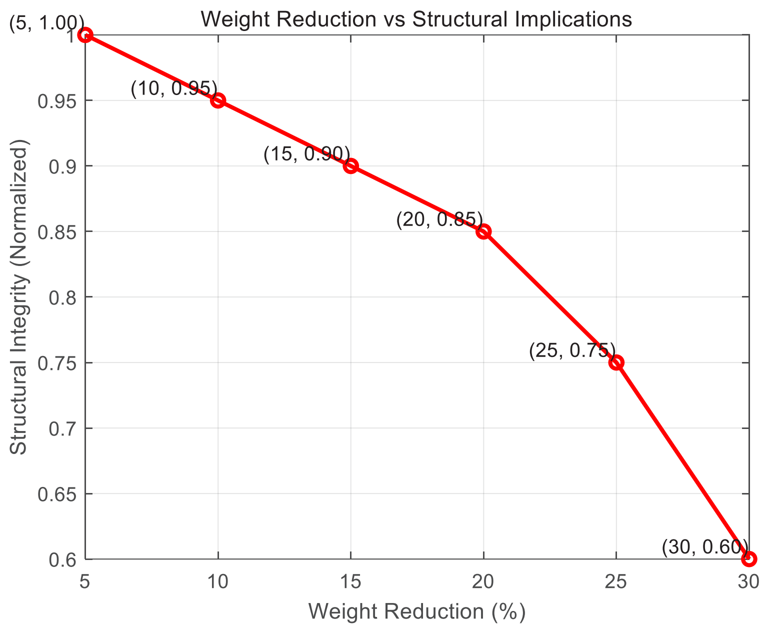

Fig. 7. The relationship between weight reduction and structural strength of a component

When the weight reduction is 5%, the structural integrity of the component is up to 1.0, and the component maintains its full strength. When the weight reduction increases to 10%, the structural integrity of the component only slightly decreases to 0.95, indicating that the component still maintains considerable strength, but the strength has begun to decrease slightly. As the weight reduction increases, this downward trend continues, and the structural integrity gradually decreases to 0.90 when the weight reduction is 15%, and gradually decreases to 0.85 when the weight reduction is 20%. As the weight reduction increases to 25%, the structural strength continues to decrease, and the structural integrity decreases to 0.75 at this time. Finally, at a 30% weight reduction, structural integrity is further reduced to 0.60, at which point the component reaches its limit of strength.

This is highlighted by the statistics in this chart, which illustrates a common problem in product design and manufacturing optimization: how to strike a balance between weight reduction and structural strength. While reducing the weight of a component can provide many benefits, such as improved fuel efficiency, improved handling or maneuverability, or enhanced performance, it also results in a loss of strength. As a component loses weight, its ability to withstand stresses and forces decreases, which can lead to potential failure or deformation, especially under extreme conditions.

This chart shows that too much weight reduction, especially beyond 25%, will lead to a significant loss of structural integrity. As the weight reduction increases, the impact on the structure becomes more and more significant, and the component will no longer perform as expected. Designers need to carefully balance the degree of weight reduction to ensure that the benefits of performance improvement are balanced against the need for structural integrity.

In real-world applications such as aerospace or automotive manufacturing, both lightness and strength are critical [18], so an optimal balance must be determined so that weight reduction does not cause fatal damage to the structural strength of the component. Data shows that a weight reduction of 15% to 20% is a good compromise, which can bring certain weight reduction benefits while maintaining sufficient structural strength. Beyond a weight reduction of 25%, further optimization may require material replacement or other design modifications to ensure the reliability and durability of components.

6 Conclusions

The present work has demonstrated an end-to-end methodology for enhancing the UAV cover injection molding process, emphasizing weight saving, deformation reduction, and mechanical strength enhancement. By closing the gap between mold design optimization and process-level improvement, we have succeeded in demonstrating for the very first time that FEA and AI-based multi-objective optimization can fundamentally enhance UAV part production. Optimization of mold geometry, material flow, and cooling distribution has led to improved part quality and consistency and the warpage and material wastage critical issues solution.

Another major contribution of this work is the development of a structurally sound lightweight mold structure as well as optimization of performance and manufacturability. The use of advanced simulation software such as MATLAB to predict material flow, shrinkage, and warpage enabled the optimization of mold design before physical prototyping, thus saving time and cost compared to the trial-and-error approach employed in traditional mold design. Through the utilization of local thinning, supported ribs, and hollow-core inserts, we were able to strike a compromise between reducing material consumption while still having sufficient strength so that it could withstand injection molding.

The AI-based multi-objective optimization also facilitated the optimization of process parameters such as injection pressure and cooling time to minimize warpage while ensuring the mechanical integrity of the UAV covers. The results have shown that parts for UAVs can be produced with improved efficiency, generating environmentally friendly production processes in the UAV industry.

While this study provides an integrated approach to UAV cover design and manufacture, there are several areas for future work. One potential area is the exploration of more advanced materials, such as lightweight composites or bio-based polymers, that might offer even better performance characteristics in terms of weight reduction and strength. Future research would be able to prioritize the AI algorithm-based optimization techniques [19], including other parameters such as material wear, long-term lifespan, and environmental factors into the optimization process.

An additional area of future research is to extend the application of this work to other components of the UAV, wings and fuselage, where similar weight reduction and strength concerns are also present. Also, integrating real-time monitoring systems into the injection molding process has the ability to feed back and enhance the molding process and quality of the part on a continuous basis [20].

Lastly, the benefits realized in this study provide the foundation for the development of more efficient, sustainable, and high-performance UAV systems. With the application of UAVs growing across various industries, the ability to design and produce parts that are both lightweight yet structurally strong will play a key role in achieving enhanced performance and reducing the cost of manufacture.

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