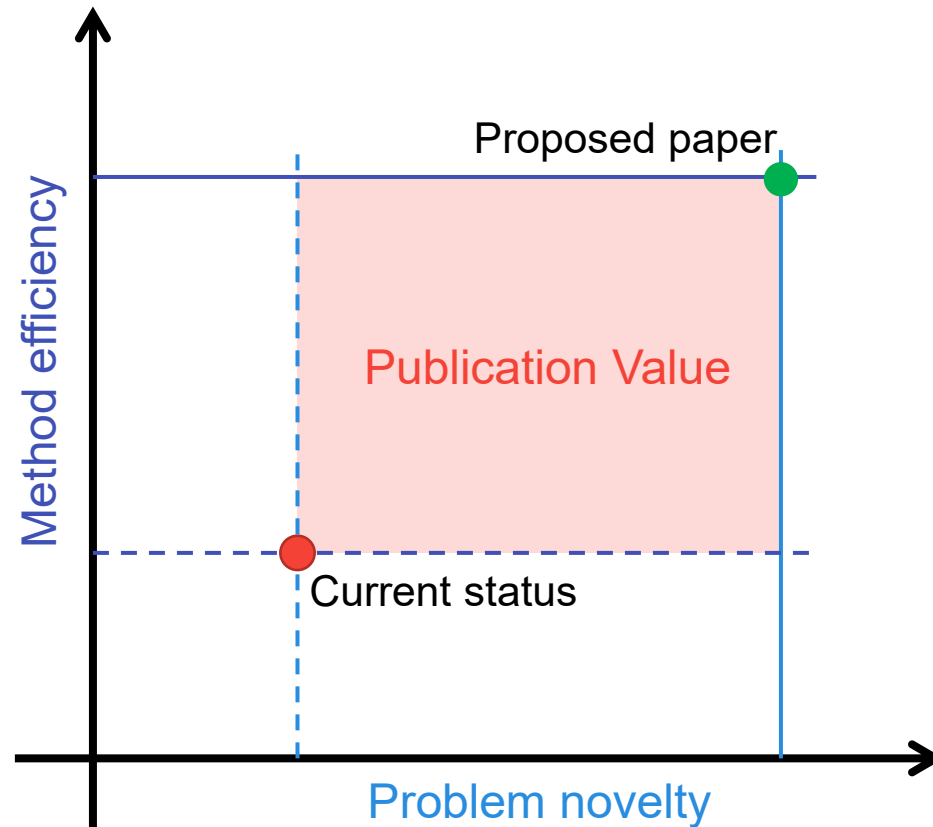


How to write a good journal paper

Maxim Tyan

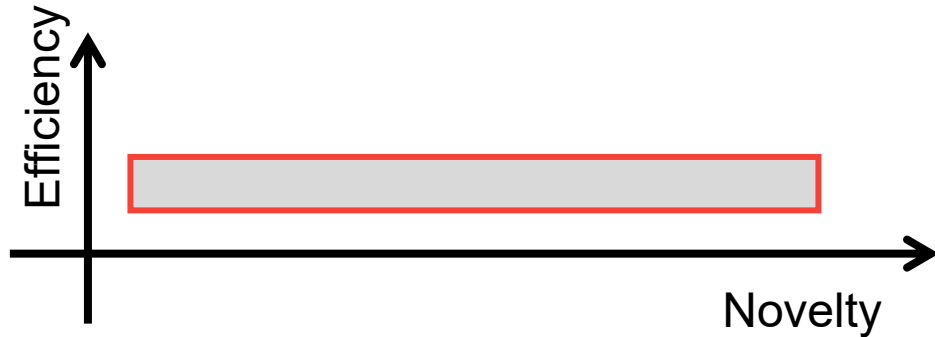
2023-01-05

Good Paper: efficient way to solve a new problem

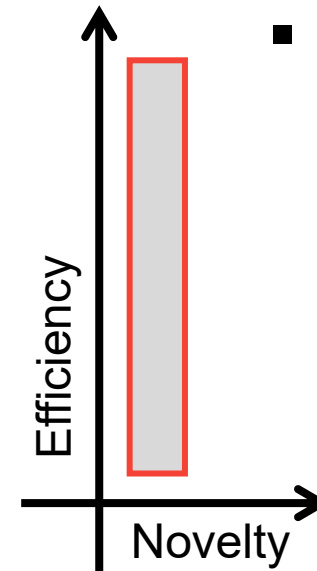


- Good journal paper must identify an important problem to solve and show an efficient way to solve it
- Very important to show the current status of the problem through literature review

Novelty vs Efficiency



- Usually focus on **applications**
- Minimum improvement on hot topics
 - Now
 - UAM, eVTOL, certification, UTM
 - Digital Twin
 - Hydrogen propulsion, Environment friendly
 - 10 years ago
 - Artificial intelligence, Machine learning
 - Drones, eVTOL-UAV



- Usually focus on **fundamental research**
- Need more efficient methods for old problems
 - Conventional aircraft design
 - MDO
 - Surrogate modeling
 - Discipline analysis (aero, CFD, propulsion, performance)

Journal Paper is not a Report!

	Report	Journal Paper
Problem	Given by a project / class	Need to justify why the problem is important
Methods	Detailed description of methods, derivation, validation	Focus only on important features. Keep enough details to understand the methods
Results	May include all the results. If necessary, attach results as a separate files.	Show only results that will highlight the method's features, strong points and issues

- *The problem*
- *How we solved it*

- *The problem*
- *Importance of the problem*
- *How we solved it*
- *Benefits of our solution*

Typical Report Structure

- Problem definition
 - What do we solve?
 - What data is available?
 - What should we get?
- Methods used
 - Algorithms, tools, procedures
- Results
 - Full results
 - Discussion
- Conclusions / Summary

Typical Journal Paper Structure

- Literature review (Introduction)

- What problem do we solve?

Problem must be clear

- Where does the problem come from?
- Is the problem new?
- Why is it important to solve the problem?
- What other people did to solve the problem?
- What are strong and weak points of other methods?

- Methods

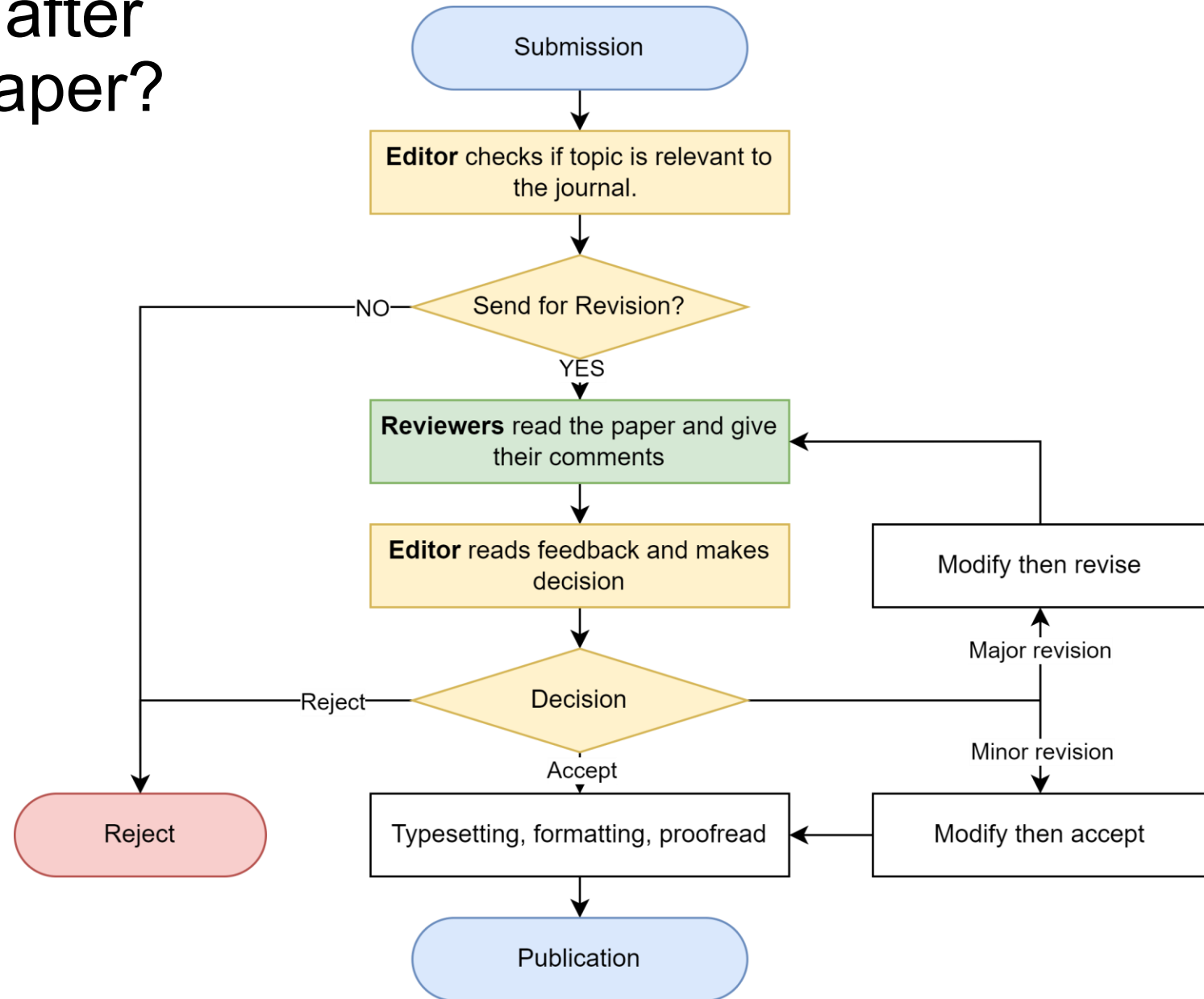
- Clearly show how you can solve the problem
- Show how you can outperform existing methods

- Results

- Must support the problem statement
- Must provide a metric to benchmark the new method vs. old

- Conclusions

What happens after you submit a paper?



Who are editors and reviewers?


- Usually, volunteers. Don't get paid for the work
- Can spend little time for review (1-3 hours)
- Don't have time to read the paper in detail



- The paper must be clear!
 - All the important details must be presented
 - No need for irrelevant information
 - All discussions must be supported with results

A good title and abstract are 50% of success

- Title must be specific and clearly describe the paper
- If title is too general or doesn't cover the contents of the paper, editor can make wrong decision without revision
- Better to keep the title within 10-12 words



FOCUS

Keep Focused on Efficient Problem Solving

- Clearly explain the problem
- Text, result or figures must support the solution of the problem
- Don't write about other problems too much
- Identify what parameter can be improved. Focus on it!
 - Example: New method improves accuracy of propeller analysis.
 - What parameters represent propeller analysis? -> thrust, torque (T, Q)
 - Explain how you calculate, show results of analysis, show validation of these parameters. Don't show too much other parameters. Don't blur the focus

Example of paper title evolution (now writing)

1. Research on Enhanced Fidelity Analysis Modeling and Prediction Method for Propulsion System of eVTOL UAVs
2. Methodology Development of Calibration and Prediction for eVTOL UAV Propulsion Analysis using Wind Tunnel Data
3. A Novel Methodology for eVTOL UAV Propulsion Analysis Calibration using Wind Tunnel Data
4. Development of Calibration Methodology using Wind Tunnel Tests for Performance Prediction of Electric Propulsion Systems with Wide Range of Component Specifications

Paper must be consistent!

■ Terminology:

- Don't use different words with similar meaning.

■ Equations and variables

- Same variables must be used.
 - If electrical power is P_e it must be it! Not P_{el} , P_{elec} , p_e
- Use nomenclature for equations and terminology. This can be deleted later.

■ Paper merits

- Keep the same parameters for comparison, validation and discussion. Don't use parameters with similar meaning.
 - If you measure Absolute error, use only it. Don't use relative, RMSE or other metrics without need.
 - If measuring accuracy of Motor Power prediction. Compare motor power! Don't compare torque, RPM or power coefficient!
 - RPM, rpm, RPS, n, ω , Ω – choose only one!

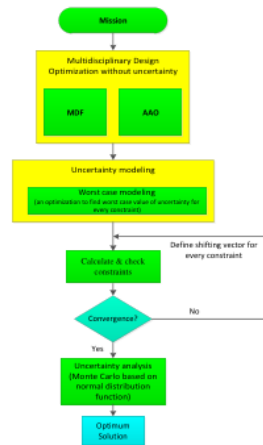
Professional Look

Good looking paper has more chances for publication

- The work must look professional. It indicates to editor and reviewers that authors are serious and put a lot of efforts to publication.
- Figures must be created with same style
 - Application used (python, excel, matlab, inkscape, drawio)
 - Font size, grids, line widths
 - Avoid too much pictures and color
- Equations must look like equations

Examples of Unprofessionally Looking Work

385 E, Payload Specifications, V_s, R_s)
 386 & Uncertainty value ($U=[U_v, U_{UC}, U_{w}, U_{cb}, U_{cl}, U_v, U_p]$)
 387 for $i=1, 2, \dots, n_i$
 388 & Optimum Parameters: $X_w, C_w, C_{wv}, b_w, R_a, L_a, A_w, C_{at}, C_{it}, b_{it},$
 389 $A_H, C_{Hv}, C_{Hv}, b_H, A_H, i_H, Z_H, i_H, L_H, L_A, \theta_H,$
 390 $\Gamma_H, \theta_H, \Gamma_H, Z_H, W_F, T, n$
 391 4. Lack of convergence: If the uncertainties violate the possibility of the answer a shifting vector
 392 of the answers appropriate for the violated constraint must be found for feasibility. For example,
 393 if the constraints related to flight time requirements is not met The difference between the
 394 required fuel and the available fuel will be added to the available fuel (required fuel is the output
 395 of movement Simulation). Then step 3 is carried out again.
 396 The UAV multidisciplinary optimal design algorithm in the presence of uncertainties decoupled
 397 approach is presented in figure 2.



398 Figure 2 - UAV multidisciplinary design optimization algorithm in the presence of uncertainties (decoupling
 399 approach)

Mixed equations and text.
 Variables not aligned. Too
 bright color for a paper.

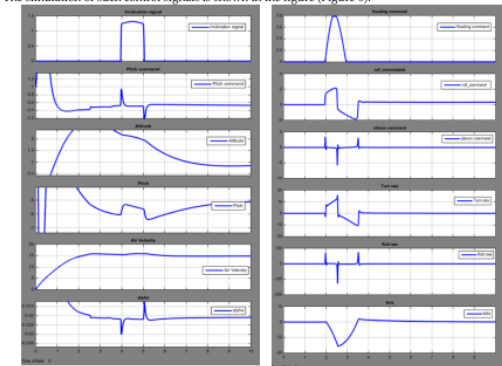
421 Table 1- outputs of design code for global hawk redesign

Section	Real value	MDF (without uncertainty)	Decoupling approach(with uncertainty)	Nested approach(with uncertainty)
Wing span (m)	39.9	39	39	40
Wing area (m ²)	63.02	68.2	68.25	68.6
Body diameter (m)	1.42	1.28	1.3	1.4
Body length (m)	14.5	14.5	14.5	14.48
Empty mass (kg)	5868	5229	5538	5646
Takeoff mass (Kg)	14628	12159	14133	14826
Error percent of Takeoff mass compared to Real value	-	17%	3%	1%
Propellant mass (kg)	7400	5570	7235	7820
Run time to optimization (Sec)	-	21507	23107	51000
percentage of success by Monte Carlo analysis	-	51%	100%	100%

422 As can be seen the success rate of optimal response obtained from MDF algorithm (without
 423 uncertainty) is 51%, from decoupled method is 100% and from the nesting method is 100% (Of
 424 course 100% of the probability of the uncertainties ($3\sigma=99.7\%$)). The code execution time in
 425 the nested method is 30,000 seconds longer than MDF algorithm (without uncertainty) and in the
 426 decoupled method is 1600 seconds longer than MDF algorithm (without uncertainty). The total
 427 mass obtained from nested method is 2667 kg more than the total mass of MDF algorithm and
 428 the total mass of decoupled method is 1974 kg more than the total mass of the MDF algorithm.
 429 The total mass obtained from the optimum design algorithm, in the presence of uncertainties in
 430 the nested method is 14.8 tons and in the decoupled method is 14.1 tons. This means that to
 431 compensate for the failure rate in multidisciplinary optimization algorithm without the presence
 432 of uncertainties the mass has increased so that the success rate increases from 51% to 100%.
 433 Considering the uncertainty is bringing answers closer to the real case. As a result, regardless of
 434 the uncertainty, however the design is more optimal it is not reliable. If the amount of
 435 uncertainty changes the impact on the total mass of the design is shown in figure 4.
 436

Colored table in a paper

Aerospace 2020, 7, x FOR PEER REVIEW 8 of 10
 157 Figure 5. Diagram of the UAV control architecture.
 158 The processing of the obtained flight and the video stream of flight test data at the Przasnysz
 159 airfield provide an opportunity to optimize control signals to pitch, roll, yaw servos of follower UAV.
 160 The simulation of such control signals is shown in the figure (Figure 6).



161 Figure 6. Reaction of the follower UAV as a response to changing of the flight parameters of the
 162 leading UAV.

163 As seen from Figure 4, the simulation results of the system practically have no errors in the
 164 output parameters of the flight, as well as being provided with a minimum overshoot and oscillation.

7. The trajectory building for a group flight

165 The UAV's group control strategy basically includes the three following types of group
 166 behavior: master-slave method, virtual leader method, and behavior control [6]. In this paper we
 167 consider the behavior of the group as the master-slave method which keeps track due to the geometric
 168 center of the leading UAV. In this method the leading UAV follows the navigation object, the other
 169 UAV's should be following for the leader.

170 While detecting and tracking the leading UAV in the frame, we can save the relative distances
 171 and angles between the group members in order to maintain it. The reference trajectory is rigidly
 172 connected with the supporting reference points in the navigation module (Figure 7). Thus, we can
 173 get the desired position of the UAV in the formation:
 174

$$\begin{bmatrix} x_i^d(k) \\ y_i^d(k) \end{bmatrix} = \begin{bmatrix} x_r(k) \\ y_r(k) \end{bmatrix} + \begin{bmatrix} \cos \Psi(k) & \sin \Psi(k) \\ -\sin \Psi(k) & \cos \Psi(k) \end{bmatrix} \begin{bmatrix} x_i^{dr}(k) \\ y_i^{dr}(k) \end{bmatrix}, \quad (16)$$

175 where $x_i^{dr}(k), y_i^{dr}(k)$ are the relative distance between the desired position and the ideal
 176 trajectory consisting of the reference points $x_r(k), y_r(k)$.

PrintScreen of figures –
 poor resolution, unreadable
 text, very bad print quality

Examples of Professionally Looking Work

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ALEXANDROV ET AL.

expensive design optimization with simulations. The approach integrates the convergence techniques of nonlinear programming with the use of variable fidelity models available in engineering disciplines. We work with first order (i.e., derivative based) optimization methods because they are generally more efficient and can handle larger numbers of design variables and a broader range of models than methods that do not rely on derivatives.

In this paper we describe the idea that underlies first order AMMO and give three specific examples of adapting nonlinear programming algorithms in the AMMO framework. Computational demonstrations follow. The paper concludes with lessons learned and open questions under investigation.

First-Order AMMO Methodology

In this work the design optimization problem is represented by a nonlinear program of the form

$$\begin{aligned} & \text{minimize} && f(x) \\ & \text{subject to} && c_1(x) = 0 \\ & && c_2(x) \geq 0 \\ & && x_L \leq x \leq x_U \end{aligned} \quad (1)$$

where the evaluation of the objective function and constraints involves a high fidelity simulation for a multidisciplinary problem, a set of coupled simulations, with each analysis a particular aspect of the physical system or the behavior of a subsystem. Some constraints can involve physical states (responses) of the system, whereas others can be algebraic or purely geometrical.

To solve Eq. (1), AMMO relies on the trust region approach¹¹ in nonlinear programming to ensure robust behavior. Conventional derivative based nonlinear programming algorithms, including trust region methods, solve a sequence of subproblems, each of which operates on local first- or second-order Taylor series, with various approximations to the first and second derivatives of the contributing functions. The information exchange between the analysis and the optimizer is depicted at the top of Fig. 1.

If evaluating the functions and derivatives involves a simulation of high accuracy but high computational cost (e.g., the Navier-Stokes equations), the repeated consultations with the analysis required by the optimizer are expensive.

In AMMO we expand the idea of a local model by replacing the Taylor series in the subproblems with general models that have local trends that are similar to those obtained with high-fidelity analyses. AMMO builds models for the sequence of optimization subproblems using high-fidelity and low-fidelity information. The models are constructed so that their trends are similar locally to the trends in the high-fidelity model. This is accomplished by requiring that the models in the optimization subproblems be consistent to first order with the high-fidelity model, as follows.

Let f , c_1 , and c_2 be low-fidelity models of f , c_1 , and c_2 , respectively. At each iteration i , of an AMMO algorithm, the low-fidelity

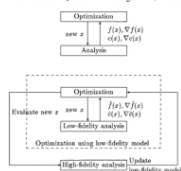


Fig. 1 Conventional optimization vs. AMMO.

models are required to satisfy first-order consistency with the high-fidelity counterparts, i.e.,

$$\begin{aligned} \hat{f}(x_k) &= f(x_k) & \nabla \hat{f}(x_k) &= \nabla f(x_k) \\ \hat{c}_1(x_k) &= c_1(x_k) & \nabla \hat{c}_1(x_k) &= \nabla c_1(x_k) \\ \hat{c}_2(x_k) &= c_2(x_k) & \nabla \hat{c}_2(x_k) &= \nabla c_2(x_k) \end{aligned} \quad (2)$$

Higher-order consistency conditions can be imposed for problems with available higher-order derivatives.

Conditions (2) ensure that \hat{f} , \hat{c}_1 , and \hat{c}_2 mimic the local behavior of first-order Taylor series approximations of f , c_1 , and c_2 around the current design x_k . First-order consistency is easily obtained in practice. The work reported here uses a technique we call the β -correction, due to Chang et al.¹² Given a high-fidelity function ϕ_0 (say, f) and any low-fidelity model ϕ_1 of ϕ_0 , we correct ϕ_1 , as follows. Define

$$\beta(x) = \frac{\phi_0(x)}{\phi_1(x)}$$

and construct the linear approximation

$$\hat{\beta}_1(x) = \beta(x_k) + \nabla \beta(x_k)^T (x - x_k)$$

Then

$$\hat{\phi}_1(x) = \hat{\beta}_1(x) \phi_1(x)$$

satisfies the consistency conditions (2). Other simple correction schemes are available to enforce consistency.

Optimization subproblems in the AMMO framework, depicted at the bottom of Fig. 1, operate on corrected low-fidelity models. Expensive, high-fidelity computations serve to recalibrate the low-fidelity models occasionally, based on a set of systematic criteria, to obtain \hat{f} , \hat{c}_1 , and \hat{c}_2 . The salient features of AMMO can be summarized as follows:

1) Although a low-fidelity model may not capture a particular feature of the physical phenomenon to the same degree of accuracy (or at all) as its high-fidelity counterpart, a low-fidelity model may still have satisfactory predictive properties for the purposes of finding a good direction of design improvement. Locally, imposing the first-order consistency (2) ensures this property.

2) AMMO replaces the local Taylor series of conventional optimization by general nonlinear models required to satisfy the consistency conditions (2). In principle, AMMO is capable of handling arbitrary models, provided the easily imposed consistency conditions are satisfied.

3) AMMO is based on the trust-region approach, which can be described as an adaptive move limit strategy for improving the global behavior of optimization algorithms based on local models. The trust-region methodology ensures the convergence of the AMMO scheme to a solution of the high-fidelity problem¹¹ by providing a measure of the low-fidelity model's predictive behavior, a criterion for updating the model, and a systematic response to situations in which an optimization phase performed using a low-fidelity model gives either an incorrect or a poor prediction of the high-fidelity model's actual behavior.

Practical efficiency of any particular AMMO scheme depends on the predictive quality of the corrected low-fidelity models for the purposes of optimization, which, in turn, are problem-dependent.

AMMO Under Study

The first-order AMMO approach can be used in conjunction with any gradient-based optimization algorithm and any suite of variable-fidelity models. In the remainder of the paper, we describe specific instances of first-order AMMO based on three nonlinear programming algorithms. This discussion will give a prospective user an idea of how to adapt a particular nonlinear programming technique to the AMMO framework.

The three algorithms under study follow the trust-region scheme. Each algorithm solves a sequence of optimization subproblems that operate on models of the objective function and constraints within a trust region where the model trends are thought to approximate

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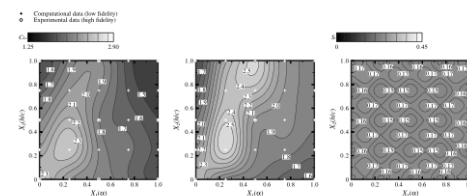


Fig. 5 Cokriging regression constructed with 12 FCD experimental samples and 57 FFD computational samples: a) cokriging regression, b) kriging interpolation for low-fidelity data, and c) total uncertainty.

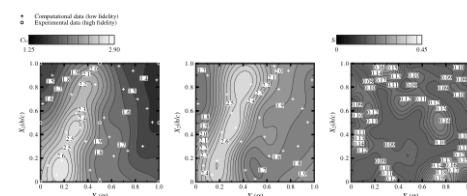


Fig. 6 Cokriging regression constructed with 12 FCD experimental samples and 25 LH computational samples: a) cokriging regression, b) kriging interpolation for low-fidelity data, and c) total uncertainty.

is induced by the suppression of systematic error, the small λ_k leads to a marginal difference between the regression and interpolation models. Cokriging regression, however, has the potential to reduce the effect of systematic error in conjunction with the randomization. Furthermore, blocking is also used with PCD to obtain the high-fidelity experimental data, aiming to reduce systematic error in addition to the randomization. PCD can block systematic error between block boundaries by orthogonal blocking. Although estimating the amount of systematic error reduction via the combination of randomization, regression models, and blocking is difficult due to the number of sources, those effects have been statistically proven [24,25].

In addition to systematic error, the experimental data used contain random error, and replication is performed at the center point of the PCD used. The replication provides deviation of the samples as 0.02 with 95% confidence, indicating that 95% of new samples should lie within a random error of ± 0.02 . Since the replication is performed only at the center point, the samples around the edge may contain random errors, and thus low confidence. The deviation analysis, however, indicates relatively small random error compared with the

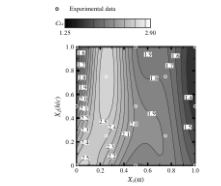


Fig. 7 Target response map constructed with 17 experimental samples built by kriging regression.

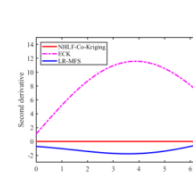


Fig. 8 Second derivative of the discrepancy function for different approaches in demonstration example 1

4.1.2 Example 2: Two-level MF surrogate model with three sets of LF data

To further validate the effectiveness of the NHEF-Co-Kriging method with more than two sets of LF data, a two-level MF surrogate model with three sets of LF data which is modified from Ref. [48] is considered, whose formulation of the HF model and three LF models are as follows

$$\begin{aligned} y^* &= (6x - 2)^2 \sin(2x - 4) \\ y_1^* &= 0.5y^* + 10(x - 0.5) + 5 \\ y_2^* &= 0.4y^* - x - 1 \\ y_3^* &= 0.3y^* - 10x + 6 \\ 0 &\leq x \leq 1 \end{aligned} \quad (47)$$

Fig. 6 (a) shows the actual functions of the four models. Same as the demonstration function in Example 1, 5 HF and 10 LF sample points generated by LHS are $X_1 = [0.1437, 0.28159, 0.5309, 0.7062, 0.9640]$ and $X_2 = [0.0266, 0.1457, 0.2154, 0.3875, 0.4423, 0.5440, 0.6091, 0.7281, 0.8527, 0.9779]$, respectively. Three LF models share the same set of LF sample points. The MF surrogate models constructed based on the HF and LF samples are shown in Fig. 6 (b).

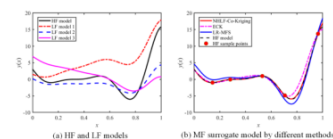


Fig. 6 True model and MF surrogate model of the demonstration example 2

- Equations aligned properly
- Flow charts are black-and-white
- Figures of proper size and resolution
- Figures have legends, titles
- Text in figures is approximately same size and the paper text