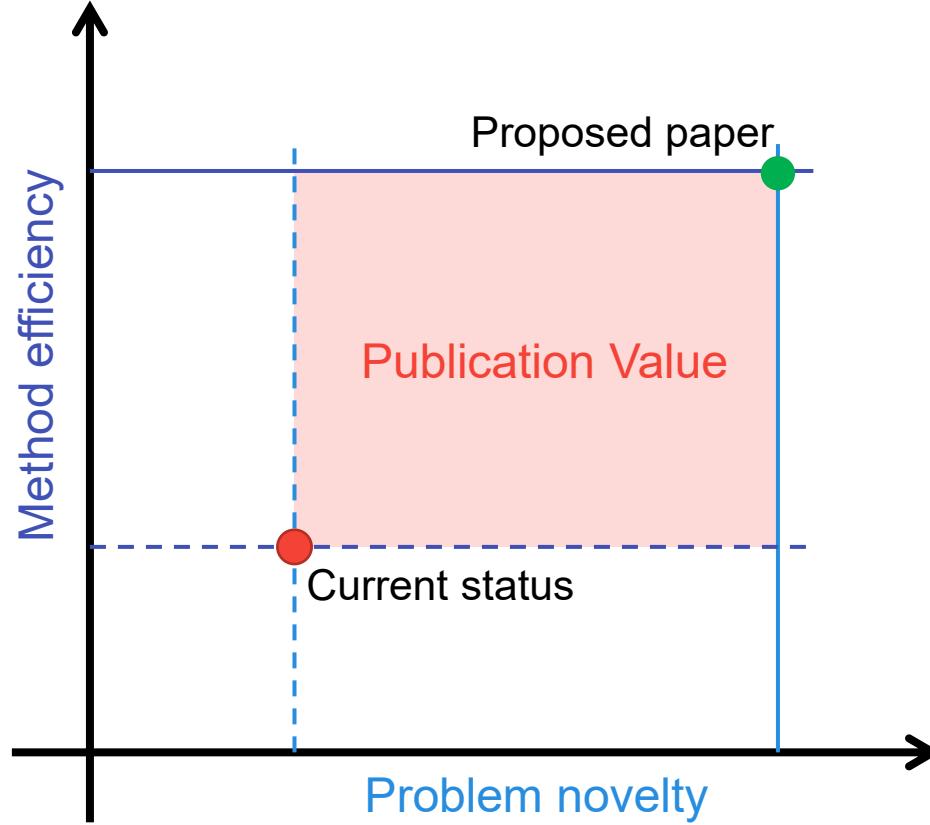


How to write a good journal paper

Maxim Tyan

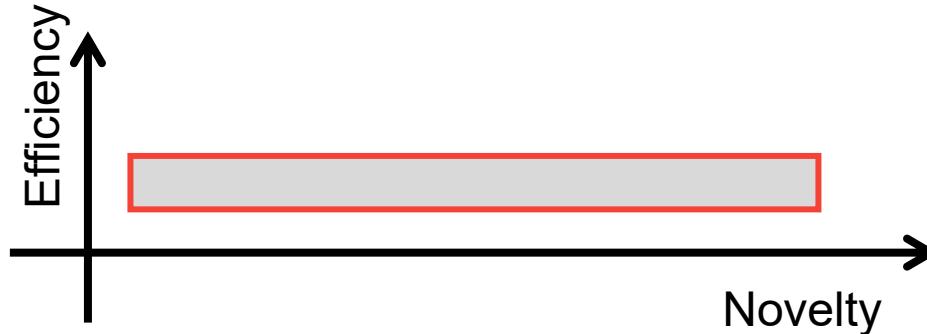
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Good Paper: efficient way to solve a new problem

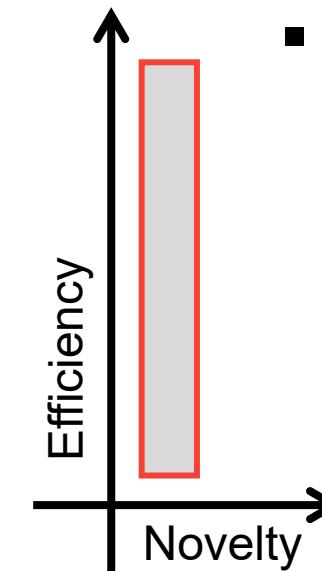


- Good journal paper must identify an important problem to solve and show an efficient way to solve it
- Very important to show the current status of the problem through literature review

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

Report:

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

Journal Paper:

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

Typical Report Structure

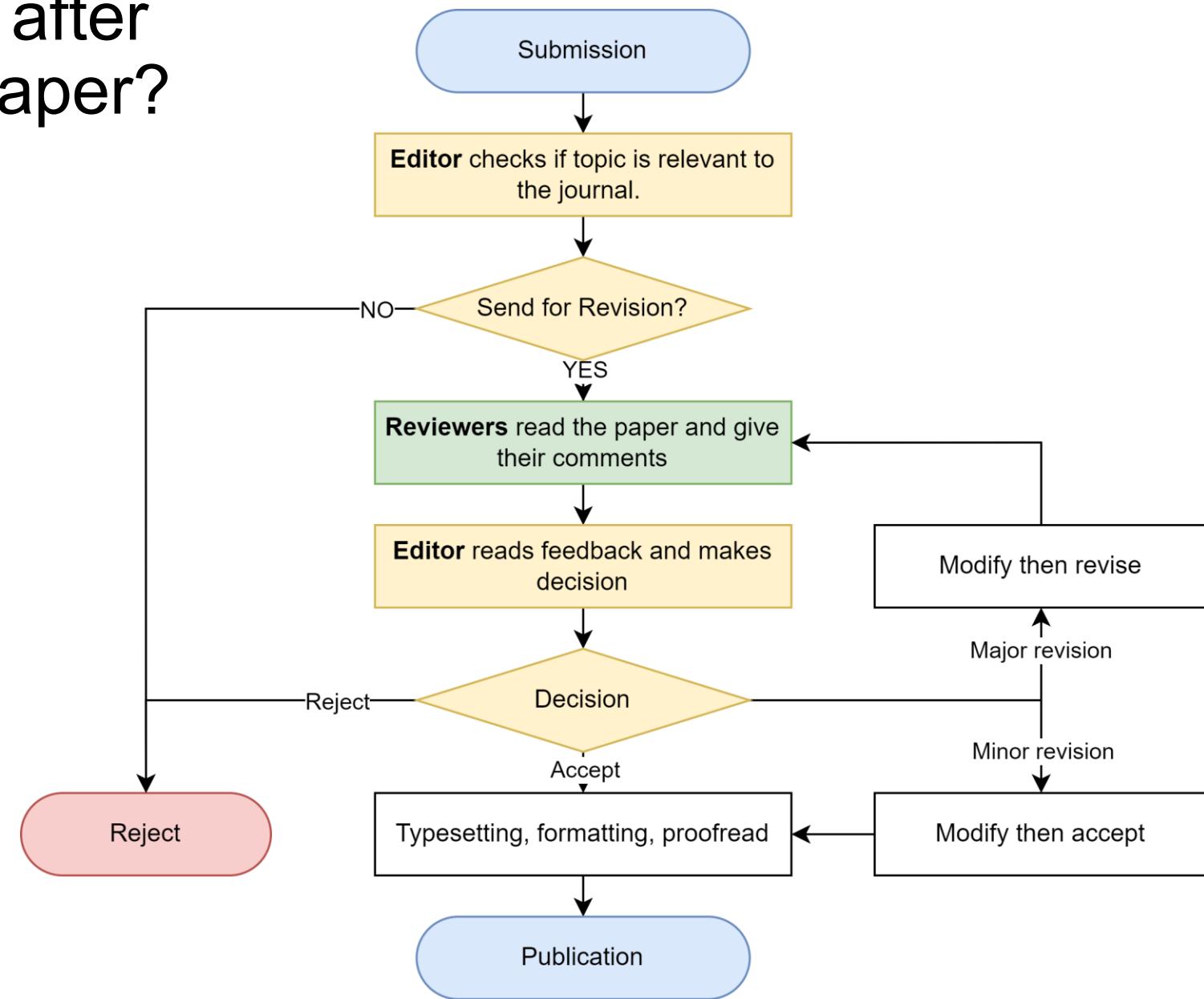
- Problem definition
 - What do we solve?
 - What data is available?
 - What should we get?
- Methods used
 - Algorithms, tools, procedures
- Results
 - Full results
 - Discussion
- Conclusions / Summary

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_3 , R_N
 386 & Uncertainty value ($U_i = \{U_{T_i}, U_{S_i}, U_{W_i}, U_{C_i}, U_{L_i}, U_{F_i}\}$)
 387 for $i=1, 2, \dots, n$
 388 & Optimum Parameters: X_W , C_{IW} , C_{IW} , b_W , R_B , L_B , A_H , C_{HT} , C_{HT} , b_H ,
 389 A_H , C_V , C_V , b_V , A_F , b_F , Z_W , w , j_W , L_A , θ_F ,
 390 θ_H , θ_H , F_H , Z_C , 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.

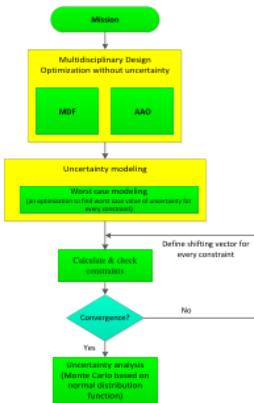


Figure 2 • UAV multidisciplinary design optimization algorithm in the presence of uncertainties (decoupling approach)

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

Section	Value			
	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%

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

Colored table in a paper

Figure 5. Diagram of the UAV control architecture.

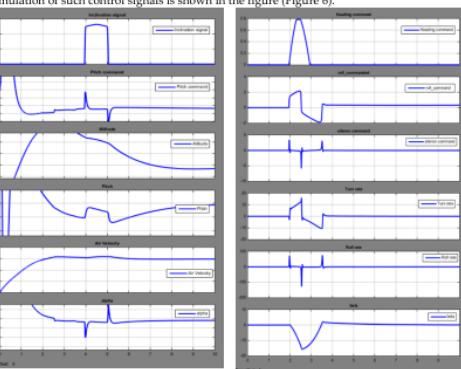


Figure 6. Reaction of the follower UAV as a response to changing of the flight parameters of the leading UAV.

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

7. The trajectory building for a group flight

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

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

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

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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ALEXANDRIN ET AL.

expense of design optimizations with simulations. The approach integrates the convergence techniques of nonlinear programming with the use of variable-fidelity models available in engineering disciplines. We want to emphasize that AMMO is not a new optimization method because they are generally more efficient and can handle larger numbers of design variables and a broader range of models than methods based on gradient information.

In this paper we describe the idea that underlies first-order AMMO and give three specific examples of adaptive nonlinear programming algorithms based on it. The paper concludes with conclusions 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

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

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

To solve such problems, we use the trust-region approach¹¹ in nonlinear programming to ensure robust behavior. Conventional derivative-based nonlinear programming algorithms, including trust-region methods, are based on Taylor series expansions of which operates on local first- or second-order Taylor for series, with various approximations to first and second derivatives of the constraints and the objective function. The trust region approach is the one that optimizes the local Taylor expansion of the objective function.

11) Although a low-fidelity model may not capture a particular feature of the physical phenomena to the same degree of accuracy as the high-fidelity counterpart, a local low-fidelity model may have a good direction of design improvement. Locally, imposing the first-order consistency (2) on the local Taylor expansion.

2) AMMO extends the idea of local Taylor expansion of conventional optimization for general nonlinear models required to satisfy the convergence criteria (2). In principle, AMMO is capable of handling arbitrary models, provided the first- and second-order 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 convergence of the AMMO scheme to a local minimum of the high-fidelity problem by using a measure of the low-fidelity model's predictive behavior, a criterion for updating the model, and a systematic recourse to situations in which the low-fidelity model fails. In addition, a local low-fidelity model gives either an incorrect or a poor prediction of the high-fidelity model's actual behavior.

These three steps of any particular AMMO scheme depend on the predictive qualities of the corrected low-fidelity models for the purposes of optimization, which, in turn, are problem dependent.

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

$$\begin{aligned} f_i(x_k) &= f_i(\bar{x}_k) & \nabla f_i(x_k) &= \nabla f_i(\bar{x}_k) \\ c_i(x_k) &= c_i(\bar{x}_k) & \nabla c_i(x_k) &= \nabla c_i(\bar{x}_k) \\ \dot{c}_i(x_k) &= \dot{c}_i(\bar{x}_k) & \nabla \dot{c}_i(x_k) &= \nabla \dot{c}_i(\bar{x}_k) \end{aligned} \quad (2)$$

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

Conditions (2) ensure that \bar{x} , \dot{x} , and \ddot{x} mimic the local behavior of the high-fidelity model at the center point of the trust region and the current design x_k . First-order consistency is easily obtained in practice. The work reported here uses a technique we call the β -corrector, due to Chang et al.¹² Given a high-fidelity function ϕ_h (say, f) and a low-fidelity model ϕ_l of ϕ_h , we correct ϕ_h as follows. Define

$$\hat{\phi}(x) = \phi_h(x)\phi_l(x) \quad (3)$$

and construct the linear approximation

$$\hat{\phi}_L(x) = \hat{\phi}(x_k) + \nabla \hat{\phi}(x_k)^T(x - x_k) \quad (4)$$

Then,

$$\hat{\phi}(x) = \hat{\phi}_L(x)\phi_h(x) \quad (5)$$

satisfies the consistency condition (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. Experimental data points are used to build the low-fidelity models occasionally, based on a set of systematic criteria, to obtain \bar{x} , \dot{x} , and \ddot{x} . 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 phenomena to the same degree of accuracy as the high-fidelity counterpart, a local low-fidelity model may have a good direction of design improvement. Locally, imposing the first-order consistency (2) on the local Taylor expansion.

(2) AMMO extends the idea of local Taylor expansion of conventional optimization for general nonlinear models required to satisfy the convergence criteria (2). In principle, AMMO is capable of handling arbitrary models, provided the first- and second-order 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 convergence of the AMMO scheme to a local minimum of the high-fidelity problem by using a measure of the low-fidelity model's predictive behavior, a criterion for updating the model, and a systematic recourse to situations in which the low-fidelity model fails. In addition, a local low-fidelity model gives either an incorrect or a poor prediction of the high-fidelity model's actual behavior.

These three steps of any particular AMMO scheme depend on the predictive qualities 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 suitable variable-fidelity models. In the remainder of the paper, we describe specific instances of first-order AMMO based on three nonlinear programming algorithms: a trust-region method, a sequential quadratic programming algorithm, and a genetic algorithm. These three algorithms provide an idea of how to adapt a particular nonlinear programming technique to the AMMO framework.

The first example we study follows 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 tends to approximate

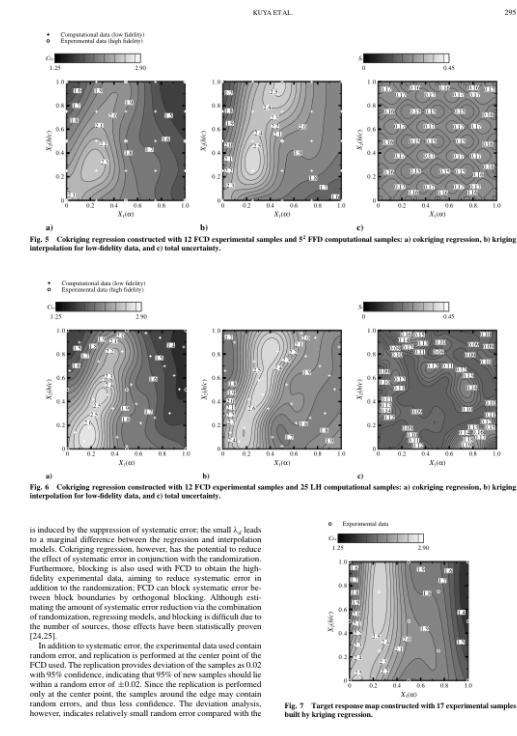


Fig. 1 Conventional optimization vs. AMMO.

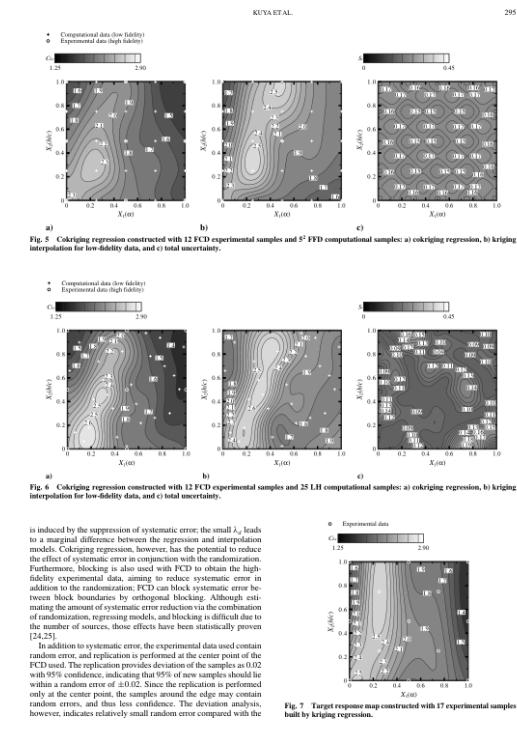


Fig. 2 Kriging regression constructed with 12 FFD experimental samples and 5⁵ FFD computational samples: a) kriging regression, b) kriging interpolation for low-fidelity data, and c) total uncertainty.

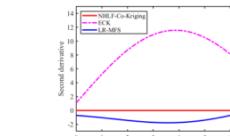


Fig. 3 Second derivative of the discrepancy function for different approaches in demonstration example 1

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

To further validate the effectiveness of the NLH-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

$$\begin{aligned} y^0 &= (6x - 2)^2 \sin(12x - 4) \\ y^1 &= (0.5x^3 + 10x - 0.5)^2 + 5 \\ y^2 &= 0.4x^3 - x - 1 \\ y^3 &= 0.3x^3 - 10x + 6 \\ 0 \leq x \leq 1 \end{aligned} \quad (47)$$

Fig. 6 (a) shows the actual functions of the four models. Same as the demonstration function in Example 1, 1.5 HF and 10.1F sample points generated by LHS are $X_h = [0.1437, 0.28159, 0.5309, 0.7062, 0.9640]$ and $X_f = [0.0266, 0.1457, 0.2154, 0.3875, 0.4423, 0.5440, 0.6911, 0.7281, 0.8527, 0.9779]$, 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).

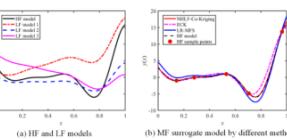


Fig. 4 Kriging regression constructed with 12 FFD experimental samples and 25 LH computational samples: a) kriging regression, b) kriging interpolation for low-fidelity data, and c) total uncertainty.



Fig. 5 True model and MF surrogate model of the demonstration example 2

Fig. 6 (a) HF and LF models

Fig. 6 (b) MF surrogate model by different methods

Fig. 6 (c) Target response map constructed with 17 experimental samples built by kriging regression.

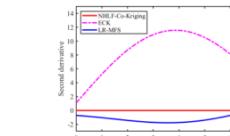


Fig. 7 Target response map constructed with 17 experimental samples built by kriging regression.

- 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