RAMDO Machine Learning for Virtual Product Development

RAMDO SOLUTIONS

www.ramdosolutions.com

1 Virtual Product Development (VPD)

Manufacturing companies are facing increased competition and demands for faster time-to-market, higher performance & reliability, reduced product development risk, and cost-effective design of their product. The traditional build–test–redesign–retest cycle can be expensive and stretch the development schedule very long.

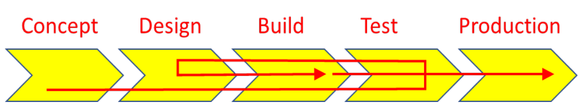


Fig. 1 Traditional Product Development

At an early stage of the product development process, the impacts of design change on performance and cost-effectiveness are high; and the cost of design change is low. Thus, it is very desirable to take advantage of the early stage to achieve Virtual Product Development (VPD). The benefits of VPD are substantial, with reduced development costs, significantly fewer physical prototypes, and drastically shortened development schedules.

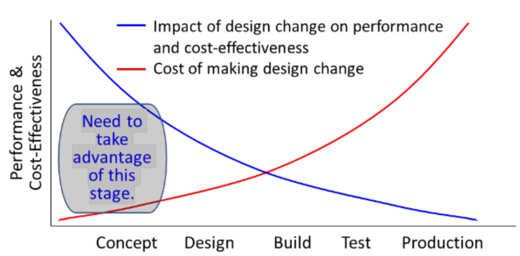


Fig. 2 Design Decision Early in the Process

Physics-based simulation will help us better understand the behavior of the product and eliminate design problems, while we can observe only behavior of the product from physical testing. Moreover, the physics-based simulation model can be used for design optimization to ensure higher product quality and reduced product cost, whereas it is quite difficult to sequentially optimize a design using physical testing.

To develop an effective VPD, the physics-based simulation model needs to be validated, as shown in Fig. 3, so it can correctly represent the product attributes. Concurrently, the validated simulation model needs to be available early during concept development, which is an impossible requirement.

Most engineering designs today are derivatives of previous designs, meaning they do not start from a blank slate. Thus, previously validated simulation models can be stored in the database management and version control system for development of the next-generation product. When a next-generation product is to be developed, the relevant simulation model in the database should be updated for new content. Thus, a very good simulation model for new product design can be rapidly provided to the VPD process for speedy product development time and reduced cost. The updated and improved simulation model can be used to obtain a reliability-based optimal design.

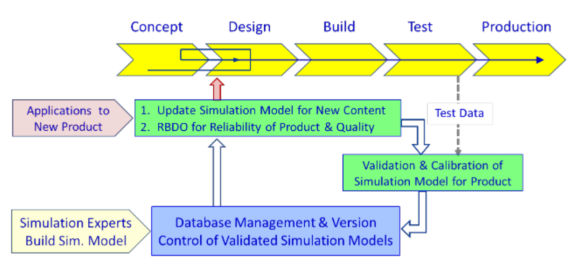


Fig. 3 Virtual Product Development (VPD)

In addition, during the product development process, when the next-generation product testing data become available, the updated simulation model can be validated for further enhancement and stored in the database management and version control system for development of the future-generation product.

In VPD, RAMDO will play a key role by providing machine learning models for uncertainty quantification (UQ), verification & validation (V&V), calibration, and reliability-based design optimization (RBDO) as shown in Fig. 4.

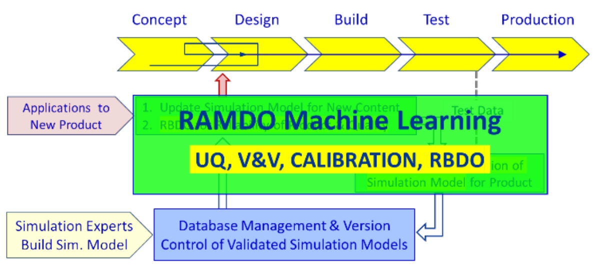


Fig. 4 RAMDO's Key Role in VPD

Effective use of RAMDO will provide benefits for VPD: (1) faster product development, (2) reduced product development costs, (3) fewer physical prototypes, (4) increased product reliability, (5) reduced warranty costs, and (6) higher customer satisfaction. This article will introduce RAMDO capabilities in the following sections.

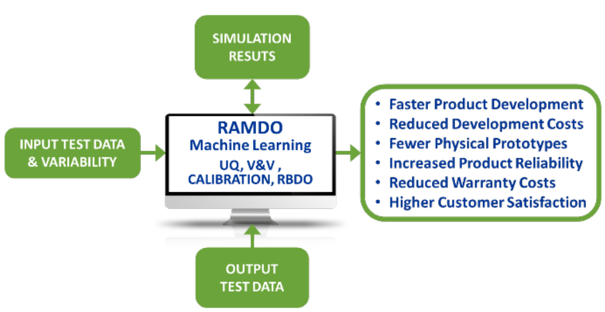


Fig. 5 Benefits of RAMDO for VPD

2 RAMDO

RAMDO is an engineering software tool that enhances computer simulation models using machine learning models to carry out UQ, V&V, calibration, and RBDO. For this purpose, RAMDO can be interfaced with all simulation software tools.

2.1 Uncertainty Quantification (UQ)

UQ enables engineers to account for variability of input variables/parameters by efficiently generating the simulation outputs as statistical distributions.

UQ involves obtaining the influence of the variability of input variables/parameters to the simulation model outputs. Thus, it can quickly become computationally too expensive to evaluate all possible scenarios. Therefore, machine learning models are desirable to approximate actual simulation model outputs.

RAMDO UQ's unique accuracy and efficiency comes from the **RAMDO Machine Learning** models:

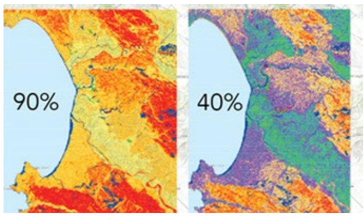
(1) **Dynamic Kriging™ (DKG)** is part of **RAMDO Machine Learning** models that automatically selects the optimum Kriging model from 54 different Kriging models for the given application problem.

(2) **Variance Window™** is RAMDO's design of experiments (DOE) method that selects a specific subset of input parameter domains that minimizes DOEs needed to achieve accurate results efficiently.

DKG is used as a very efficient substitute for having to run large numbers of expensive simulations. Coupled together DKG, the Variance Window, and the adaptive sequential DOE sampling process form **RAMDO Machine Learning** models that is the key to **RAMDO UQ** for obtaining highly accurate results very efficiently.

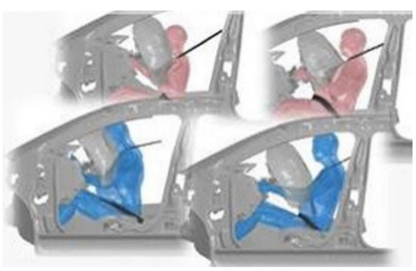
2.1.1 RAMDO UQ for Predictive Mobility Map[1]

RAMDO UQ was used in conjunction with terramechanics (soil and ground vehicle wheel interaction) simulations to create accurate and reliable predictive stochastic mobility maps for the Next Generation NATO Reference Mobility Model for off-road vehicle mobility. UQ was carried out and reliability assessment was made for Speed Made Good and GO/NOGO decisions for the ground vehicle based on the input variability models of the terrain elevation and soil property parameters. It was found that the deterministic map of the region of interest had a probability of only 25% to achieve the indicated speed. The accurate Speed Made Good maps will provide reliable information and confidence to the decision maker for navigation.



2.1.2 RAMDO UQ for Crash Simulation to Predict Population Risk[2]

RAMDO UQ was used in conjunction with vehicle crash simulation software to predict human populations most at risk for injury. Since people come in so many shapes and sizes, it is difficult to design a passenger restraint system that will accommodate everyone. Previous models were only able to account for the average size male in passenger restraint designs, thus leaving several population segments at higher risk for injury. These results will provide engineers with a tool to reliably predict which human populations are more at risk for injury in vehicle crashes, guiding the design of passenger restraint systems to protect more lives.



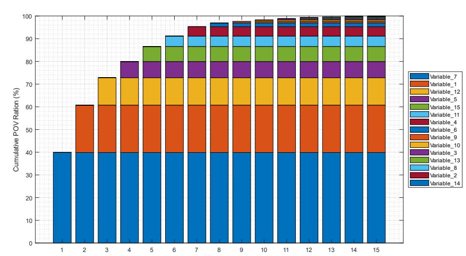
2.2 Variable Screening

Carrying out UQ using machine learning models could be computationally intensive if the number of input variables is large. To reduce computational time, the **RAMDO Variable Screening** method provides engineers with a tool for identifying whether some insignificant input variables could be removed. **RAMDO Variable Screening** will rank order input variables based on their statistical impact on the output performance distributions. Often, using **RAMDO Variable Screening**, engineers may find a number of input variables that could be removed without impacting the output variances.

In addition, identification of important input variables may help the manufacturer to improve product quality by paying close attention to the variabilities of those high ranking variables during the manufacturing processes, while potentially saving manufacturing cost without diminishing the product quality.

2.2.1 RAMDO Variable Screening for Washer Simulation

RAMDO Variable Screening was applied to a washer door simulation model for deflection with 15 input variable variabilities. Among 15 variables, **RAMDO Variable Screening** identified the top 8 variables (variables 7, 1, 12, 5, 15, 11, 4, and 6) that cover more than 97% of the total output distribution, as shown in the figure below. The other 7 variables altogether have 3% influence on the output distribution and thus possibly can be removed when the **RAMDO Machine Learning** model is constructed and **RAMDO UQ** is carried out.



Rank	Var. Num.	POV Ratio	Cumulative POV
1	7	39.86%	39.86%
2	1	20.89%	60.75%
3	12	12.08%	72.82%
4	5	7.11%	79.93%
5	15	6.64%	86.57%
6	11	4.57%	91.15%
7	4	4.10%	95.25%
8	6	1.71%	96.96%
9	9	0.70%	97.65%
10	10	0.59%	98.25%
11	3	0.55%	98.80%
12	13	0.51%	99.31%
13	8	0.34%	99.64%
14	2	0.31%	99.95%
15	14	0.05%	100.00%

2.3 Verification & Validation

RAMDO V&V enables engineers to statistically validate their simulation models. For this, the simulation output distribution must be validated against testing data of the product before it can be used in VPD with confidence. However, often only a limited number of testing data is affordable to obtain.

In **RAMDO V&V**, the uncertainty due to limited testing data is quantified via a Bayesian approach and possible candidates of output distributions are obtained, and the target output distribution is selected at the posterior median. The Target Output distributions are good approximations of true output distributions.

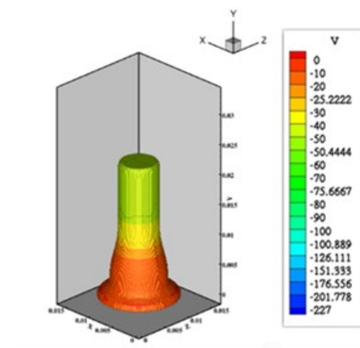
The target output distribution is used as benchmark for quantitative validation of the simulation model. To account for the limited data, **RAMDO V&V** provides two quantitative validation measures: simulation model error ranges and confidence levels. **RAMDO Machine Learning** models are used in obtaining the error ranges and confidence levels. The quantitative validation measure should provide simulation engineers with valuable information for further improvement of their simulation models.

In addition, RAMDO provides confidence-based assessments of product reliability even when the simulation model is biased, and input and output testing data are limited.

2.3.1 RAMDO V&V for Taylor Bar Impact[3]

RAMDO V&V was used in conjunction with SCIMITAR3D software, which is a Eulerian hydrocode with Elastoplastic modeling, to predict the mushroom diameter and change of the bar length of the Taylor bar impact problem. The input variables of the simulation model included: yield stress, strain hardening constant, and strain hardening exponent. The previous approach to validate this simulation model was a pointwise comparison, which ignored the variability of the input parameters. **RAMDO V&V** included analyzing output variability and performing a model validation that helped engineers confidently compare simulation output distribution with the target output distribution.

Using **RAMDO V&V**, the most probable error of the simulation model prediction of the mushroom diameter was 6.46%. On the other hand, the most probable error of the simulation model prediction of the deformed length was 2.37%. Thus, the simulation model predicted the length change better than the diameter change.



2.3.2 RAMDO V&V for Offshore Platform Panel[4]

RAMDO V&V was used in conjunction with ANSYS topology optimization & FEA to analyze an offshore platform panel structure design. To investigate performance of the optimized design, it was manufactured using a 3-D metal printing and tested with a Universal Testing Machine (UTM) under a compression load. The previous approach used only three simulations and three experimental data points to validate the model, leaving engineers with an unknown level of accuracy and confidence in the model's predictions. Using **RAMDO V&V**, the most probable error of the simulation prediction model was 5.37%. On the other hand, if we accepted an error below 6%, the confidence level of the simulation model acceptance was 99.37%.

2.4 Calibration

While carrying out V&V, the simulation engineers may discover their simulation model output distributions do not agree with the target output distributions so that the simulation model cannot be validated. This could be due to the simulation model being biased. In this case, the simulation model needs to be investigated by the simulation model experts for possible cause of the biasness and improve it.

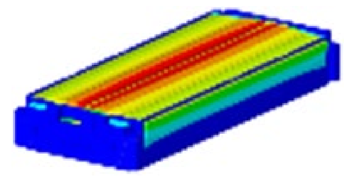
On the other hand, the bias could be due to inaccurate statistical information of some input parameters or variables due to lack of input data. In this case, **RAMDO Calibration** can be used to obtain the statistical information of the input parameters or variables by minimizing the Hellinger distances between the simulation output distributions and target output distributions.

For computational efficiency, **RAMDO Calibration** is comprised of sequential deterministic & probabilistic calibration methods. In the probabilistic calibration, the mean and standard deviation are optimized to minimize the cost function, which is the Hellinger distance that measures the distance between the target output distribution and simulation output distribution,

For another application, simulation models are often built based on some simplifications and assumptions. In some cases, the simplified simulation model may include parameters that do not exist in the physical model. These parameters often play an important role in helping the simulation model to correctly predict the response of the physical system. Thus, **RAMDO Calibration** should be used to identify means and standard deviations these parameters.

2.4.1 RAMDO Calibration for Battery Vibration

RAMDO V&V was used to perform validation of a charged battery simulation model for natural frequencies with input distributions of PAD compression strain, U-frame thickness and cell elastic modulus. It was found that the simulation model of the natural frequency was biased when compared to the target output distribution obtained from testing results. Before calibration, **RAMDO Variable Screening** identified the PAD compression strain as the most important variable. Thus, **RAMDO Calibration** was used to calibrate the PAD compression strain mean value and standard deviation. The calibrated PAD compression strain mean value and standard deviation were confirmed to be correct in testing of the charged battery, as the PAD compression strain is increasing when the battery is charged.



2.5 Reliability-Based Design Optimization

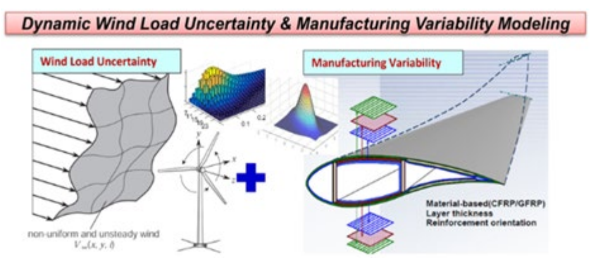
One of the important key benefits of the VPD (*i.e.*, simulation-driven product development), in contrast to the traditional product development, is that a reliable optimum design can be obtained. **RAMDO RBDO** helps engineers to find an optimum design satisfying target reliabilities, under input variability, in a highly efficient manner.

In the RBDO model for reliable design, the mean values of the random input variables are usually used as design variables, and the cost is optimized subject to the prescribed probabilistic constraints by solving a mathematical nonlinear programming problem for reliability.

RAMDO RBDO works in conjunction with all simulation software tools, enabling engineers to define variability of the input variables. **RAMDO Machine Learning** models drastically reduces the required simulation runs needed to perform RBDO, producing highly accurate results at a much lower computational cost.

2.5.1 RAMDO RBDO for 5-MW Wind Blade[5]

RAMDO RBDO was applied to a 5-MW wind turbine blade for designing reliable as well as economical wind turbine blades for 20-year service life. Dynamic wind load uncertainty models were developed using 249 groups of wind data obtained from a large spatiotemporal range to consider wind load variation. Meanwhile, the cost of composite materials used in the blade was minimized by optimizing the composite laminate thicknesses of the blade. In order to obtain the RBDO optimum design efficiently, deterministic design optimization (DDO) was carried out first using the mean wind load obtained from the wind load uncertainty models. Then RBDO was initiated from the DDO optimum. During the RBDO iterations, fatigue hotspots were carefully identified along the laminate section points. Using **RAMDO RBDO**, an optimum design of the 5-MW wind turbine blade was obtained, satisfying the target reliability of 97.725%.



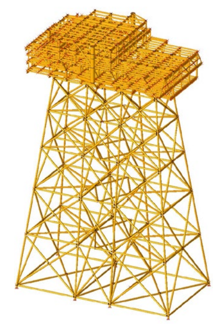
2.5.2 RAMDO RBDO for Offshore Platform[6]

Traditionally, designing an offshore platform is done by following rules and codes of the classification society. **RAMDO RBDO** was used for optimization of an offshore platform considering uncertainties from environmental loads, material properties, and manufacturing tolerances. Compared to the rules and standards, return periods are from zero to infinite years.

The target offshore platform location was the North Sea where the water depth is 130m. Variabilities exist in environmental conditions such as winds, waves, and currents. The topside weight is over 20,000ton. The supporting structure weight is 132,311ton, which is to be minimized.

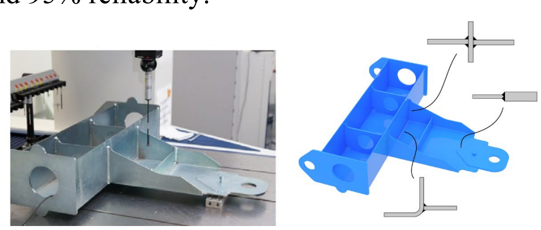
References were utilized to determine the statistical characteristics of environmental conditions such as distribution type, distribution parameters, mean, and standard deviation.

Design constraints were unity check values, which are the ratios of acting stresses and allowable stresses. The DDO model had 74 design variables and 91 constraints. The RBDO model had 37 design variables and 8 constraints. An optimum weight of 84,723ton, which was a reduction to 64.03% of the initial design weight and the target reliability of 99.865% was achieved.



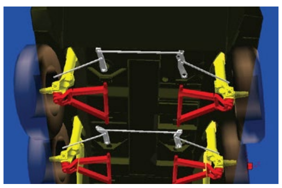
2.5.3 RAMDO RBDO for Welded Structure for Fatigue[7]

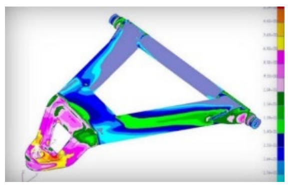
RAMDO RBDO was used to minimize the weight of a welded structure and to meet the required reliability of 95% for fatigue life, while considering the variation in manufacturing quality. The mock-up structure consists of thin plates with structural steel S355 and thicknesses 4, 6 and 8 mm, along with MAG welding and weld class C. The measured misalignments at welds are represented by statistical distributions as inputs for RBDO. The constraints are fatigue life ≥ 5 million cycles, and target reliability of 95%, max stress ≤ limit value and max displacement ≤ limit value. The 44 kg mass of the initial design was reduced to 33 kg and 55% reliability at the DDO design. After RBDO, an optimum design is obtained with a mass of 35 kg and 95% reliability.



2.5.4 RAMDO RBDO for Stryker A-arm for Fatigue

This case study shows how **RAMDO RBDO**, when used in conjunction with vehicle dynamics, finite element analysis and durability analysis, serves to improve reliability, reduce weight, and increase fatigue life for a vehicle suspension part. Using **RAMDO RBDO**, decision makers can design to meet target reliabilities resulting in safer and more reliable ground vehicles. **RAMDO RBDO** of the ground vehicle Stryker A-arm increased its fatigue life 10.8 times, achieved 97.7% target reliability, and yet reduced weight by 20% compared to the initial design.





3 Summary

An effective VPD depends on embracing simulation technology proactively early in the product process providing great value by enabling engineers to virtually explore potential product and process designs. Simulation-driven product development provides engineers with a better understanding of product performance attributes and eliminates design problems early in the product development process.

As described in this article, RAMDO machine learning models plays an ideal and very important role in the development of VPD. RAMDO has numerous capabilities that can be used in VPD of products. Using RAMDO, manufacturing industries can reduce their effort & time in development and adoption of VDP in their business since effective V&V of their simulation models and successfully obtaining reliable optimum designs are essential part of VPD.

RAMDO Solutions will strive to work diligently to be the leader in helping manufacturing industries in their successful developments of effective VPDs. RAMDO Solutions provides consulting services to customers in all disciplines. RAMDO consulting engineers have decades of experience applying RAMDO methods to a wide range of disciplines.

4 References

1. Choi, K.K., Gaul, N.J., Jayakumar, P., Wasfy, T., and Funk, M., "Framework of Reliability-Based Stochastic Mobility Map for Next Generation NATO Reference Mobility Model," *Special Issue on Sensitivity Analysis and Uncertainty Quantification, Journal of Computational and Nonlinear Dynamics*, 2018, https://doi.org/10.1115/1.4041350.
2. Gaul, N.J., Using Vehicle Driver Population Variability to Identify Population Segments with Higher Injury Risk, https://youtu.be/xaPdm97FIRI.
3. Moon, M., Sen, O., Rai, N., Gaul, N., Choi, K.K., and Udaykumar, H.S., "Confidence-Based Uncertainty Quantification and Model Validation for Simulations of High-speed Impact Problems," *ASME Journal of VVUQ*, 5(2): 021005, 2020, https://doi.org/10.1115/1.4047960.
4. Moon, M-Y., Kim, H-S., Lee, K., Park, B., and Choi, K.K., "Uncertainty Quantification and Statistical Model Validation for Offshore Jacket Structure Panel Given Limited Test Data and Simulation Model," *Structural and Multidisciplinary Optimization Special Issue*, 2019, https://doi.org/10.1007/s00158-020-02520-8.
5. Hu, W., Choi, K.K. and Cho, H., "Reliability-Based Design Optimization of Wind Turbine Blades for Fatigue Life under Dynamic Wind Load Uncertainty," *Structural and Multidisciplinary Optimization*, Vol. 54 (4), pp. 953-970, 2016, https://doi.org/10.1007/s00158-016-1462-x.
6. Kim, H-S., "Optimization via RAMDO considering Uncertainties for Marine Applications," https://youtu.be/wSnPdV0DsDI.
7. Kokkonen, P., Hemming, B., Mikkola, E., Teir, L. and Gaul, N., "Robustness optimization of welded structure to minimized mass and target fatigue life using RAMDO Petteri VTT," https://youtu.be/BHiyRzD2Upc.

Dr. K.K. Choi, CEO & Managing Member
kyung-choi@ramdosolutions.com
+1 (319) 383-5961

Dr. Nicholas Gaul, CTO & Member
nicholas-gaul@ramdosolutions.com
+1 (319) 359-6501