Optimal Ship Design and Valuable Knowledge Discovery Under Uncertain Conditions

Kalyanmoy Deb, Zhichao Lu
Dept. of Electrical and
Computer Engineering
Michigan State University
East Lansing, Michigan 48824
Email: {kdeb,luzhicha}@msu.edu

Chris B. McKesson
Dept. of Mechanical Engineering
The University of British Columbia
Vancouver, BC V6T 1Z4
Email: mckesson@mech.ubc.ca

Cherie C. Trumbach
Dept. of Management and Marketing
University of New Orleans
New Orleans, LA 70148
Email: ctrumbac@uno.edu

Larry DeCan
School of Naval Architecture and Marine Engineering
University of New Orleans New Orleans, LA 70148
Email: ldecan@uno.edu

COIN Report Number 2015004

Abstract—**Ship design is a complex engineering activity which requires a multidisciplinary consideration in arriving at design objectives and constraints. An optimal design of such problems require a multi-objective optimization method that is capable of finding multiple trade-off solutions, not only to choose a preferred solution for implementation, but also to have a deeper understanding of the interactions among design variables. In this paper, we consider two ship design models involving uncertainties in design variables, and demonstrate the usefulness of an evolutionary multi-objective optimization (EMO) method and subsequent data analysis procedures in arriving at valuable design principles that enhance the knowledge of a designer. The study is pedagogical yet provide key insights of ship design issues and importantly outlines the systematic procedure for applying the technology to other more complex design problems.**

I. Introduction

Most engineering design activities are better achieved through an optimization task in which a number of design variables are found for maximizing or minimizing one or more design goals and by satisfying a number of constraint functions. When multiple conflicting objectives are considered simultaneously, the optimization task results in a set of Pareto-optimal solutions which possess an inherent trade-off in the objectives [7].

Classical multi-objective optimization methods [16], [4] scalarize multiple objectives into a single composite objective function, which can then be optimized using a single-objective optimization method. Although such a principle can be used repeatedly to *generate* a set of trade-off solutions, studies have demonstrated that due to the absence of any parallel search ability, they are computationally expensive [20]. Proposed in the beginning of nineties, evolutionary multi-objective optimization (EMO) methods were shown to be capable of finding multiple trade-off solutions in a single simulation run [7], [6], [5], [24]. Due to their population approach and parallel search ability, EMO methods have gained an increasing popularity, particularly during the last decade.

The use of an EMO method to an engineering design problem has a number of advantages. First, as discussed above, an EMO method can find multiple trade-off designs in a single simulation. Second, the presence of multiple efficient designs allow a designer to analyze them to reveal design principles that are common to them. Since these principles are properties of high-performing designs, it is not surprising that they are valuable to the designers. This data analysis task was called as the *innovization* task by the first author [12]. Starting with manual innovization studies, the first author and his students have developed automated innovization procedures based on machine learning approaches in the recent past [2], [1], [3]. Third, EMO methods enable handling different practicalities associated with engineering design problems. One such practicality is the handling of *uncertainties* in design variables. Recent studies on robust and reliability based EMO studies have amply demonstrated their usefulness in engineering design activities [11], [10], [23], [22], [13].

In this paper, we apply the above-mentioned combination of multi-objective optimization, data analysis and uncertainty handling techniques to ship design problems. A ship design problem must be considered for a number of different objectives related to cost, weight, performance and cargo carrying abilities [26], [25]. Here, we consider two different ship design models [15], [19] and demonstrate the use of the proposed optimization and subsequent data analysis and uncertainty handling procedures to arrive at valuable insights and design principles related to optimized ships. The presence and discovery of such useful knowledge in ship design problems demonstrated in this paper should be repeated to other routine design problems.

In the remainder of this paper, we provide a brief description of the principles of existing ship design studies in Section II. The next section presents a simplistic ship design model and optimized results for two conflicting objectives of design. Thereafter, the data analysis and uncertainty handling methods demonstrate the usefulness of these procedures by revealing important design relationships among design variables and objectives. Section IV considers a more involved ship design model [19], [14] and repeats the multi-objective, data analysis and uncertainty studies to reveal further insights about ship design. Finally, Section V concludes the findings of this study.

II. Existing Studies on Optimal Ship Design

Ship design is a complicated process involving various parameters and considerations. Besides the sizing parameters which will determine the shape and size of the ship, the velocity, power needed to run the ship, fuel consumption, cargo carrying capacity, ship cost, and annual running cost are all important considerations. Although most of the above functionalities can be quantified for a ship using fluid mechanics and simplistic models [15], [19], [14], more complicated excel data based design procedure are also followed in the literature [17], [18]. In this paper, we consider two proposed mathematical models of ship design and demonstrate the use of a multi-objective design optimization methodology coupled with a reliability-based design procedure for obtaining high-performing designs. Unlike other existing studies, here we highlight a knowledge extraction procedure performed using the optimized trade-off designs to reveal useful and interesting design principles for ship design that go a long way of having a greater insight to the effect of uncertainties in designing a ship.

III. McKesson Model

In this first task, we use a simplified ship design model [15] as a bi-objective optimization problem:

$$\begin{array}{rl} \text{Minimize} & \text{ANNUAL\_COST (in \$/year)}, \\ \text{Maximize} & \text{TRANSPORT (in Tonne-miles/year)}, \\ \text{Subject to} & GM \geq 0, \\ & 5,000 \leq \text{DWT} \leq 100,000 \text{ (Tonnes)}, \\ & 12 \leq \text{Vel} \leq 22 \text{ (Knots)}, \\ & 10 \leq \text{Beam} \leq 30 \text{ (m)}. \end{array} \quad (1)$$

The variables of this problem are DWT (Tonnes), Vel (Knots), and Beam (m). The model is an intentionally simplistic model created for use as an undergraduate programming exercise. The calculation of two objective functions and constraint function GM are provided in Appendix A.

The variables of this problem are DWT (Tonnes), Vel (Knots), and Beam (m). The calculation of two objective functions and constraint function GM are provided in Appendix A.

First, we use the elitist non-dominated sorting genetic algorithm (NSGA-II) [9] to obtain a set of optimized trade-off solutions. Following parameter values are used: population size=100, number of generations=4,000, SBX crossover [8] probability p_c=1 and index $\eta_c = 15$, polynomial mutation [7] probability p_m=0.1 and index $\eta_m = 20$. Figure 1 shows these obtained trade-off solutions. Each point in the figure is a different ship configuration marking a trade-off between the two objectives: (i) Annual cost

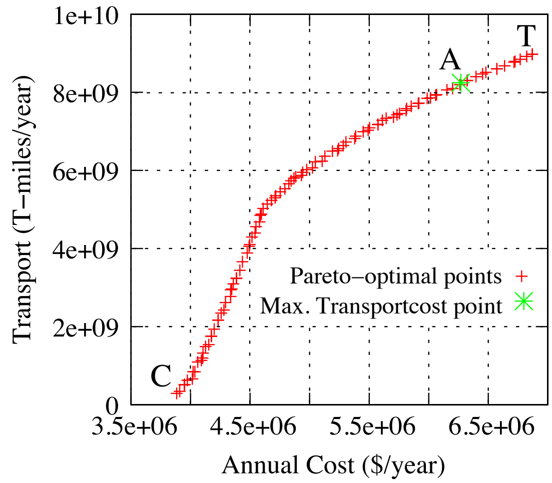

Fig. 1. NSGA-II obtained trade-off Pareto-optimal solutions for bi-objective ship design problem and a particular single-objective optimal solution.

and (ii) Transport capacity. The trade-off is clear from the plot. Solution C is best for the annual cost, but is worst for transport capacity, whereas solution T is the best for transport capacity, but comes with a large annual cost.

Some researchers avoid the complications involved in solving a multi-objective problem by forming a single composite objective using problem information. For this problem, one reasonable composite objective would be to maximize the ratio transport capacity to annual cost – a single objective function. We optimize the single-objective problem using Matlab's fmincon() algorithm and obtain a single optimal solution, marked as 'A' in the Figure 1. The single-objective treatment produces a single solution on the trade-off frontier, while a consideration of two conflicting objectives produce a set of trade-off solutions of which the single-objective optimal solution is one. Thus, a bi-objective treatment produces a number of alternative solutions, thereby allowing decision-makers to (i) understand the trade-offs exist between two or more original objectives and (ii) then choose a single preferred solution by carefully analyzing the trade-off. Such benefits of multi-objective optimization has been the main prime-movers for the increasing popularity of evolutionary multi-objective optimization (EMO) methodologies for the past two decades [7].

A. Knowledge Discovery from Optimal Solutions

The application of an EMO methodology to a design problem has now become a routine activity. But in this paper, we highlight and recommend the usefulness of two post-optimality aspects. In this subsection, we discuss the use of a recently proposed *innovization* technique [12], [2] that analyzes the obtained trade-off solutions and bring out hidden relationships among design variables and objectives as a data-mining task. Such as task is promising to provide us with a deeper knowledge about the design problem.

In Figure 2, we plot all three variable values as a function of one of the objectives (annual cost) for all obtained trade-off solutions. Following observation is made. There seems to be a phase change in trade-off solutions for

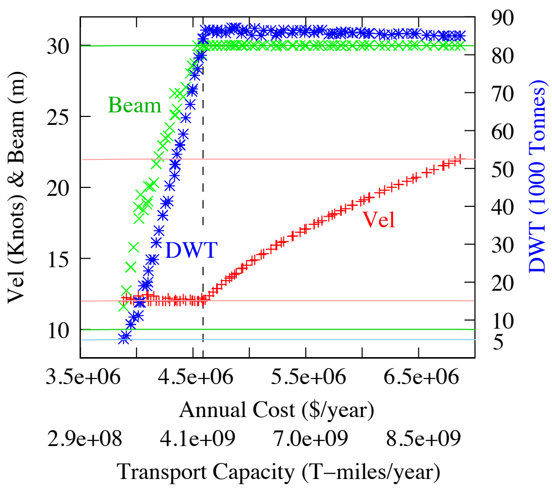

Fig. 2. Variation of three variables (DWT, Vel and Beam) for different Pareto-optimal solutions. A phase-changing pattern beyond annual cost of 4.6 M$ and a transport capacity of about 5 Billion Tonne-miles/year (dashed vertical line) is observed.

ships having an annual cost of around 4.6 M$/year and a transport capacity of about 5 Billion Tonne-miles/year (dashed vertical line). Up until this critical annual cost value, the velocity must be more or less kept constant at its lower bound at 12 Knots, but beam length must be increased monotonically from its lower bound to its upper bound for an increasing transport capacity. Thereafter, an increase in transport capacity must come from a fixed beam length of 30 m (its allowable upper bound) and a steady increase in velocity. Interesting, increased transport capacity requires a slight decreasing trend in DWT. The existence of a critical phase-changing design philosophy at a transport cost of around 5 Billion Tonne-miles/year emerges as an valuable insight for this ship design task. It is also observed that for most of these trade-off solutions, the constraint value GM is very close to zero, thereby meaning that the constraint (GM$\geq$ 0) is critical for the optimal design of the ship.

B. Handling Uncertainties and Reliable Designs

Next, we consider another important practicality in the ship design task from the point of view of uncertainties involved in adhering to the prescribed variable values in practice. Here, all three variables are considered to be uncertain using a Gaussian distribution with a standard deviation proportional to 5% of their values. That is, if the Vel is 20 Knots, it is assumed to vary normally around 20 Knots with a standard deviation of 5% of 20 Knots, or 1 Knot. Similar considerations are made for other two variables as well. The stochastic bi-objective optimization [11] becomes as follows:

$$\begin{array}{rl} \text{Minimize} & \text{ANNUAL\_COST (in \$/year)},\\ \text{Maximize} & \text{TRANSPORT (in Tonne-miles/year)},\\ \text{Subject to} & Prob(\text{GM} \geq 0) \geq R,\\ & 5,000 \leq \text{DWT} \leq 100,000 \text{ (Tonnes)},\\ & 12 \leq \text{Vel} \leq 22 \text{ (Knots)},\\ & 10 \leq \text{Beam} \leq 30 \text{ (m)}. \end{array} \quad (2)$$

The original constraint is now changed into a *chance constraint*: the probability that the constraint satisfies (that is, GM $\geq$ 0) is at least a given reliability value R. Our multi-objective optimization methodology is now changed to handle the above chance constraint using the RIA approach [11], [21].

Figure 3 shows the effect of the reliability value R on the obtained trade-off frontier. The 'Deterministic' front comes from Figure 1, where no uncertainty was considered. With an increase in reliability (R) value, the trade-off front becomes worse. That is, to have an identical transport capacity, a more reliable design demands a larger annual cost.

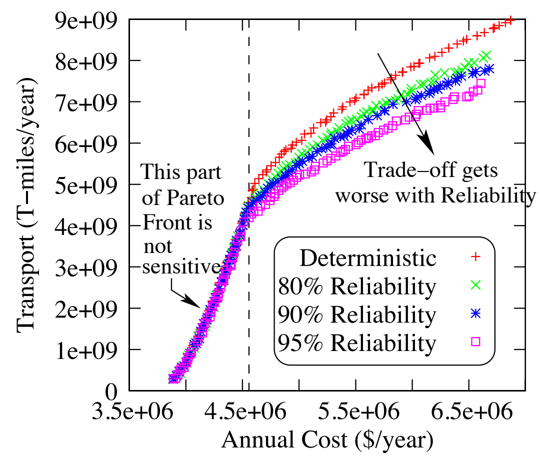

Fig. 3. NSGA-II obtained trade-off Pareto-optimal solutions for bi-objective ship design problem with uncertainty in three design parameters.

Figure 4 shows the variation of three variables for Pareto-optimal solutions with different reliability values. Following conclusions can be drawn from these solutions:

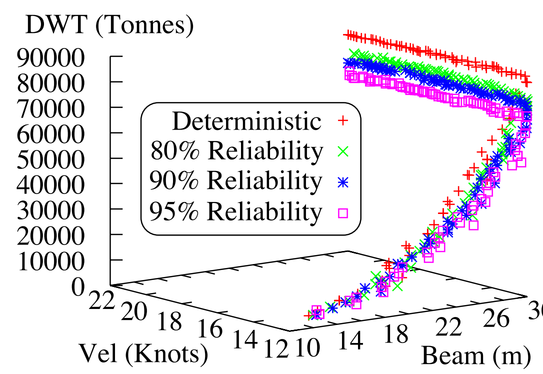

Fig. 4. Variation of three variables (DWT, velocity and beam length) for different Pareto-optimal solutions under different reliability values. Different levels of reliability comes mainly from carefully choosing the DWT variable; the other two variables do not affect the reliability of ship significantly.

1) Interestingly, uncertainties in beam length and velocity do not affect the ship's reliability against infeasibility much.
2) The main variable affecting the reliability is DWT which must be reduced with an increasing reliability requirement.

3) Additionally, a higher reliability against constraint failure comes with a decreased DWT (lighter ship). The recommended DWT values must be reduced from 85,000 Tonnes (deterministic solutions) to 79,000 Tonnes at 80% reliability or to 75,000 Tonnes at 90% reliability or down to 70,000 Tonnes at 95% reliability.

C. Increased Bound on Beam

Figure 2 indicated that the upper bound of the beam (which was fixed at 30 m) controls the phase change. Here, we investigate the effect of increasing this upper bound. We allow the beam length to be as high as 60 m and redo the above bi-objective reliability based optimization study. Figure 5 shows the new trade-off frontiers for different reliability values. The figure also

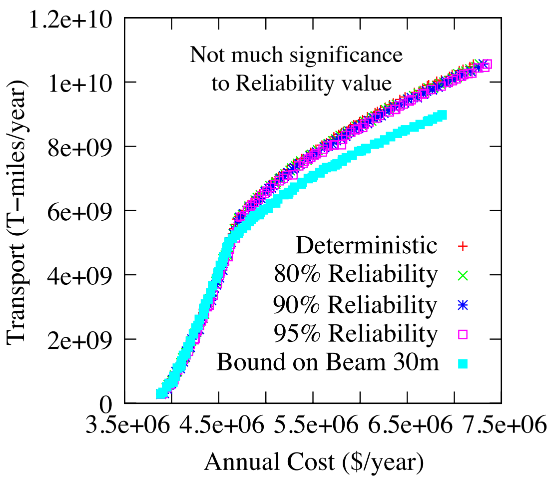

Fig. 5. NSGA-II obtained trade-off Pareto-optimal solutions for bi-objective ship design problem with uncertainty in three design parameters for an increased upper bound on beam length of 60 m.

shows the deterministic trade-off front found in the previous case with upper bound of beam being 30 m. It is clear that the relaxation of upper bound on beam allows better trade-off solutions to be found. But interestingly, now the effect of reliability of design is relatively an unimportant parameter. All fronts are similar. This is an important result indicating that there exists an optimal beam value that vanishes the sensitivity of designs due to uncertainties in the three variables.

Interesting, relaxing the beam length makes most optimal designs to reach the full effect of DWT (hitting its allowed upper bound of 100,000 Tonnes) and there is a slight difference in beam length. For the Deterministic front, optimal beam length is 31.5 m, for 80% reliability front it is 33 m, for 90% reliability is 34 m and for 95% it is 34.2 m. Interestingly, although up to 60 m Beam length is allowed, the DWT limit of 100,000 Tonnes require at most 34.2 m beam length for an optimal performance. Thus, a slight increase in beam length, from 30 to 34.2 m, made the designs insensitive to uncertainties in three design variables. Such is the power of multi-objective optimization studies. They can not only provide useful optimal variable values, but importantly can provide valuable insights about the problem, which are usually not obvious and are otherwise difficult to obtain.

IV. Sen-Bulker Ship Model

The Sen-Bulker model involves a more realistic ship design model [19]. The model has six variables, nine constraints, and three objectives, as described in Appendix B. Three objectives – minimization of light ship mass (LS), minimization of transportation cost (TC) and maximization of annual cargo capacity (AC) – are considered in our study. Although a trade-off between ship mass and annual cargo is intuitive, it is expected that the ship mass and transportation cost will be correlated. To make all objectives to be of same type, we multiply annual cargo by -1 and minimize all three objectives, although this conversion is mandatory for an evolutionary multi-objective optimization method.

First, we optimize the above problem without any uncertainty consideration. NSGA-II is used with following parameter values: Following parameter values are used: population size=100, number of generations=6,000, SBX crossover probability p_c=0.9 and index $\eta_c = 15$, polynomial mutation probability p_m=0.167 and index $\eta_m = 20$. Resulting three-dimensional trade-off solutions are shown in Figure 6. The trade-off between ship mass

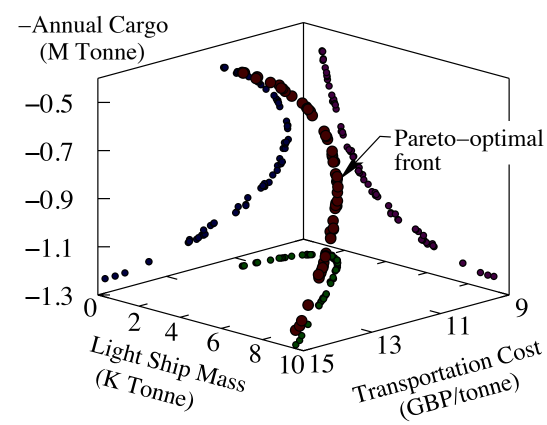

Fig. 6. Three-objective Pareto-optimal front of Sen-Bulker ship model.

and annual cargo is obvious from the z-x plane. Heavier ships are required to carry larger annual cargo. Although this is intuitive, the optimization task quantifies the trade-off exactly. It is also interesting to note the range of values of ship mass and annual cargo which constitutes the trade-off designs. The ship mass can vary between 0.905 to 9.262 K-Tonne, while the annual cargo varies from 0.5 to 1.3 M-Tonne. Table I presents the six variables

TABLE I. Three extreme optimal solutions are shown.

Best	L m	B m	D m	T m	C_B	V kts	TC £/Tn	LS K-Tn	AC M-Tn
TC	270.13	44.84	22.21	16.24	0.63	14	**9.44**	2.13	0.868
LS	196.76	31.64	15.11	11.28	0.63	14	11.33	**0.91**	0.496
AC	479.34	73.17	36.40	25.97	0.63	14	14.49	8.96	**1.241**

and corresponding objective values for the three extreme solutions.

For most part of the trade-off front, ship mass and transportation cost/Tonne of cargo values are correlated as shown by the plot in the x-y plane. For ships capable of carrying large annual cargo (more than about 0.7 M-Tonne) the ship mass and transportation costs requires a trade-off. Interestingly, although the ships with largest annual cargo carrying capacity is heaviest, but the transportation cost for carrying unit Tonne of cargo is smallest. The optimized solutions and the inherent trade-off they possess provide a plethora of interesting knowledge about ship design. After such a task, a decision-making task is needed to choose a preferred solution.

A. Knowledge Extraction from Optimized Designs

We now analyze the NSGA-II obtained trade-off solutions (a total of six variables and respective three objective values) and search for any simplistic pair-wise relationship (we refer to relevant 'knowledge' here) between the entities. Several interesting relationships are observed. We describe them next.

Figure 7 shows the relationship between two of the six variables – depth (D) and draft (T), both in m. Interestingly, there is a linear relationship preserved by these two variables for all trade-off optimized designs:

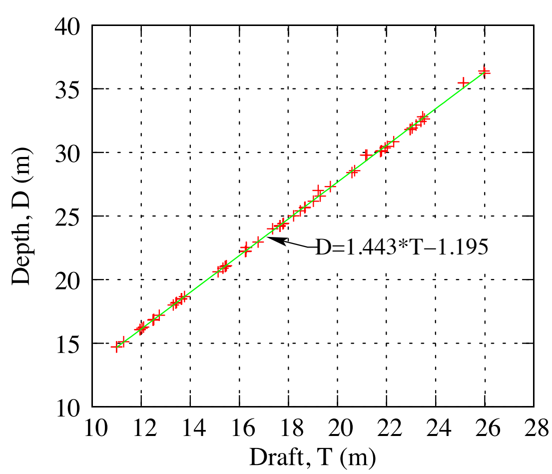

Fig. 7. Depth (D) versus draft (T) for the Sen-Bulker ship model.

$$D = 1.443T - 1.195. \quad (3)$$

As observed from the figure, a δT increase in the draft of a ship (indicating the portion of the depth which is underwater) should make a $1.443\Delta T$ increase in the depth of the ship. This is remarkable and was not something which was intuitive from the ship design model. A three-objective optimization and an analysis of obtained optimized solutions reveal such an interesting and potentially useful relationship. It indicates that any one of these two variables can be chosen by the designer. Then, the other variable value must be chosen by the above equation to come up with ships that are optimal and no other value will produce an optimal ship. Archimedes's theorem indicates that for a rectangular hollow box with an average density of $\rho(< 1)$ the following linear relationship holds:

$$D = T\frac{1}{\rho}. \quad (4)$$

A ship has a different geometry than a rectangular box and therefore the relationship is also expected to be different, but the remarkable similarity of the two equations ((3) and (4)) supports our finding.

A further analysis to the nine-dimensional data is made and it is found that two other design variables – velocity (V) and block coefficient (C_b) – must be fixed to 14 knots and 0.63, respectively, to produce optimal ship:

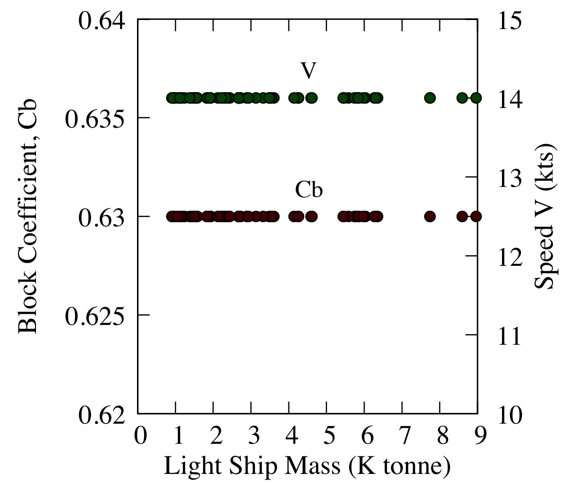

Fig. 8. Block coefficient C_b versus light ship mass for the Sen-Bulker ship model.

$$C_b = 0.63, \qquad V = 14 \text{ knots}. \quad (5)$$

It is also observed that each of the four design variables – length (L), beam width (B), depth (D) and draft (T), all in m – is correlated with the ship mass (in K-Tonne), as follows:

$$\begin{aligned} L &= 202M^{0.4}, \\ B &= 34.4M^{0.34}, \\ D &= 17.0M^{0.35}, \\ T &= 12.5M^{0.34}. \end{aligned}$$

Figure 9 makes a log-log plot of variables with the ship mass. A linear relationship in a log-log plot indicates a polynomial behavior, as stated above. The above relationship found preserved among optimized trade-off solutions can be useful in getting 'thumb-rules' or back-of-the-envelope calculations for estimating different variable values for a typical desired mass of the ship. Interestingly, for a heavier ship all four design variables must be increased in a monotonic manner. It is also obvious that in for the entire range of optimal ships, the length of the ship has the highest dimension, followed by the beam width, then the depth, and finally the draft, which is the smallest dimension.

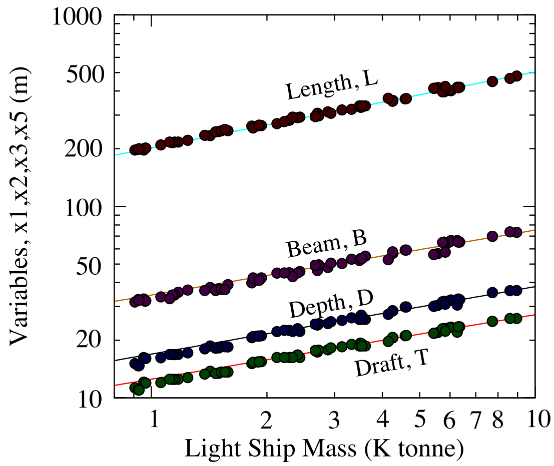

Fig. 9. Length (L), beam (B), depth (D) and draft (T) for the Sen-Bulker ship model.

B. Uncertainty in Design Variables and Knowledge Extraction

We now consider five of the six variables (except $x_4 = C_b$) to be uncertain and varying with a Gaussian distribution around their prescribed values with standard deviation of xx. Three different reliability values are used to find trade-off optimized designs. Figure 10 shows the three sets of designs on a two-objective plot. An interesting outcome is revealed: 'Larger reliability

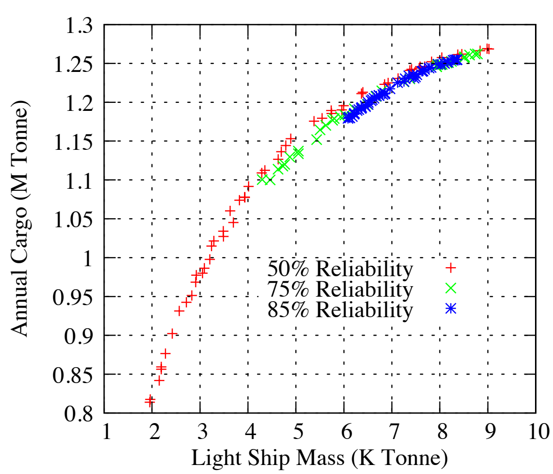

Fig. 10. Two-objective Pareto-optimal front of Sen-Bulker ship model.

comes only from a heavier ship carrying a heavier annual cargo'. Here is roughly the range of ship mass for different reliability values:

$$R = 0.85, \quad \text{mass in } [6.0, 8.5] \text{ K-Tonne},$$
$$R = 0.75, \quad \text{mass in } [4.0, 9.0] \text{ K-Tonne},$$
$$R = 0.50, \quad \text{mass in } [2.0, 9.0] \text{ K-Tonne}.$$

We now plot the four sizing variables with the ship mass to investigate for any correlation between them. We observe from Figure 11 that a higher reliability design is associated with a larger length (L) and also the length is correlated to the ship mass: $L = 207M^{0.35}$, which is

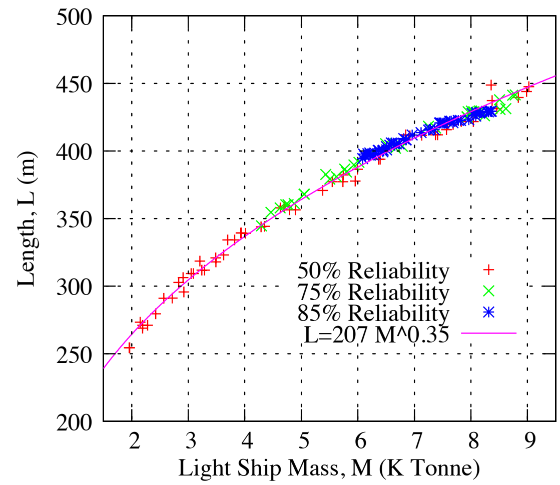

Fig. 11. Length (L) versus Ship Mass (M) for the Sen-Bulker ship model.

slightly different from that observed in the deterministic study.

A plot of beam width with ship mass in Figure 12 also reveals a similar relationship: $B = 31.5M^{0.35}$. Finally Fig-

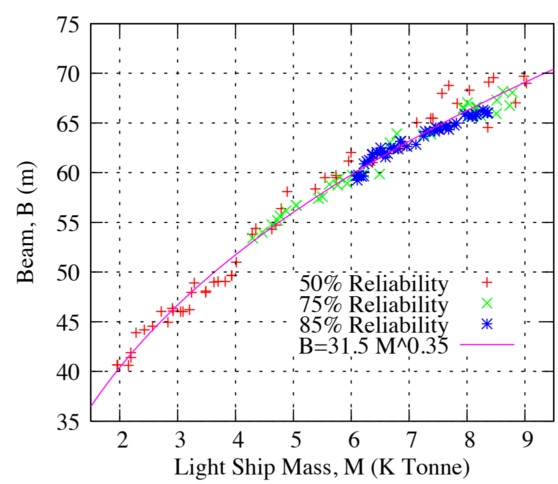

Fig. 12. Beam (B) versus Ship Mass (M) for the Sen-Bulker ship model.

ures 13 and 14 reveal the monotonic variation of depth and draft values with the ship mass: $D = 19\text{Mass}^{0.32}$. and Larger reliability values come from larger depth (D): $D = 19\text{Mass}^{0.32}$ and $T = 13.1\text{Mass}^{0.30}$, respectively. These relationships are slightly different from those obtained from the deterministic study, but account for the uncertainty in the design variables.

As we observed a direct relationship between depth and draft in Figure 7 for the deterministic case, we find a similar relationship for uncertainty-based optimized solutions with draft and length in Figure 15. The fitted relationship is $T = 0.098 + 0.057L$. These are interesting knowledge extracted from the trade-off optimized solutions, which would be valuable to the ship designers.

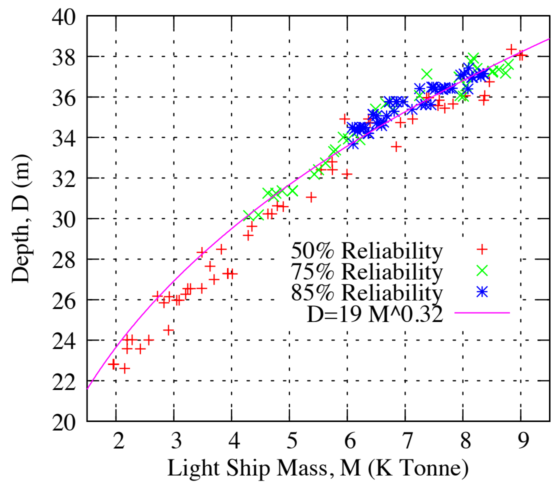

Fig. 13. Depth (D) versus Ship Mass (M) for the Sen-Bulker ship model.

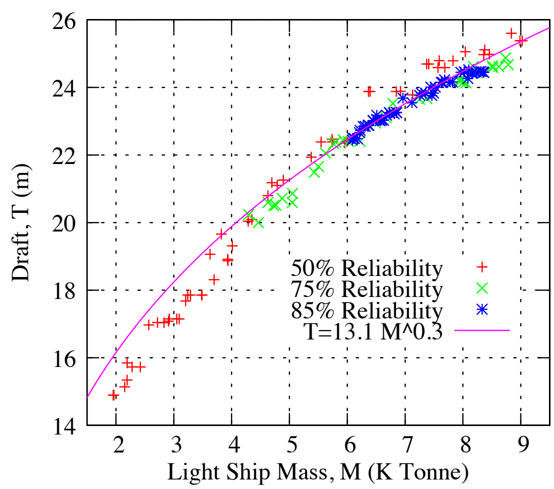

Fig. 14. Draft (T) versus Ship Mass (M) for the Sen-Bulker ship model.

V. Conclusions

Many engineering design tasks are achieved through multi-objective optimization methods in which two or more conflicting objectives are simultaneously considered for obtaining trade-off designs. In this paper, we have considered two different ship design models and optimized them using an evolutionary multi-objective optimization algorithm. The main contribution of this study has been to demonstrate two post-optimality tasks which can reveal interesting insights related to the design task. First, a data analysis procedure has been applied to the obtained trade-off optimized designs and useful design principles have been revealed. Second, some of the design variables have been considered to be uncertain and objectives have been re-optimized to find a reliable frontier of trade-off solutions. A further data analysis has revealed important insights about variables that are relatively insensitive for an increased reliability of designs.

This study demonstrates the practical importance of using multi-objective optimization and subsequent data analysis to an engineering design problem and should spur interests to designers for performing similar studies in other design activities using evolutionary methods.

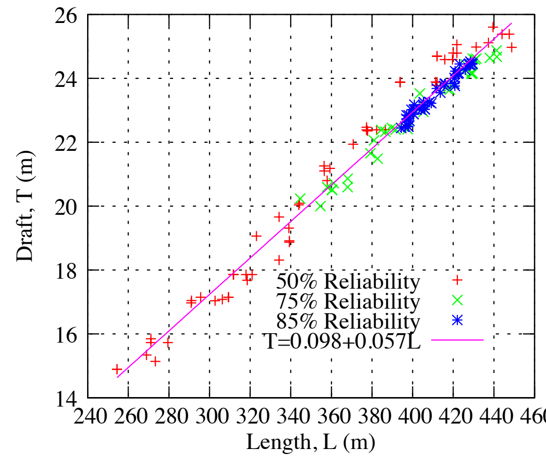

Fig. 15. Relationship between Draft (T) and Length (L) for the Sen-Bulker ship model.

Acknowledgment

Authors acknowledge the support from Office of Naval Research Award No. N00014-14-1-0814.

References

[1] S. Bandaru and K. Deb. Automated discovery of vital knowledge from Pareto-optimal solutions: First results from engineering design. In *World Congress on Computational Intelligence (WCCI-2010)*. IEEE Press, 2010.

[2] S. Bandaru and K. Deb. Towards automating the discovery of certain innovative design principles through a clustering based optimization technique. *Engineering optimization*, 43(9):911–941, 2011.

[3] S. Bandaru, C. C. Tutum, K. Deb, and J. Hattel. Higher-level innovization: A case study from friction stir welding process optimization. In *Proceedings of Congress on Evolutionary Computation (CEC-2011)*, pages 2782–2789. IEEE Press, 2011.

[4] V. Chankong and Y. Y. Haimes. *Multiobjective Decision Making Theory and Methodology*. New York: North-Holland, 1983.

[5] C. A. C. Coello and G. B. Lamont. *Applications of Multi-Objective Evolutionary Algorithms*. World Scientific, 2004.

[6] C. A. C. Coello, D. A. VanVeldhuizen, and G. Lamont. *Evolutionary Algorithms for Solving Multi-Objective Problems*. Boston, MA: Kluwer, 2002.

[7] K. Deb. *Multi-objective optimization using evolutionary algorithms*. Wiley, Chichester, UK, 2001.

[8] K. Deb and R. B. Agrawal. Simulated binary crossover for continuous search space. *Complex Systems*, 9(2):115–148, 1995.

[9] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan. A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, 2002.

[10] K. Deb and H. Gupta. Searching for robust Pareto-optimal solutions in multi-objective optimization. In *Proceedings of the Third Evolutionary Multi-Criteria Optimization (EMO-05) Conference (Also Lecture Notes on Computer Science 3410)*, pages 150–164, 2005.

[11] K. Deb, S. Gupta, D. Daum, J. Branke, A. Mall, and D. Padmanabhan. Reliability-based optimization using evolutionary algorithms. *IEEE Trans. on Evolutionary Computation*, 13(5):1054–1074, 2009.

[12] K. Deb and A. Srinivasan. Innovization: Innovating design principles through optimization. In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO-2006)*, pages 1629–1636, New York: ACM, 2006.

[13] C. K. Goh and K. C. Tan. Evolving the tradeoffs between Pareto-optimality and robustness in multi-objective evolutionary algorithms. In S. Yang et al., editors, *Evolutionary Computation in Dynamic and Uncertain Environments*, pages 457–478. Springer, 2007.

[14] S. E. Hannapel. *Development of multidisciplinary design optimization algorithms for ship design under uncertainty*. PhD thesis, Department of Naval Architecture and Marine Engineering, University of Michigan, Ann Arbor, 2012.

[15] C. McKessen, 2014. Unpublished lecture notes, "Introduction to Ship Design", University of New Orleans.

[16] K. Miettinen. *Nonlinear Multiobjective Optimization*. Kluwer, Boston, 1999.

[17] M. C. Parker. *A contextual multipartite network approach to comprehending the structure of naval design*. PhD thesis, Department of Naval Architecture and Marine Engineering, University of Michigan, Ann Arbor, 2014.

[18] M. C. Parker and D. J. Singer. Flexibility and modularity in ship design: An analytical approach. In *Proceedings of the 11th International Marine Design Conference (IMDC 2012)*, 2012.

[19] P. Sen and J.-B. Yang. *Multiple Criteria Decision Support in Engineering Design*. Springer, 1988.

[20] P. Shukla and K. Deb. On finding multiple Pareto-optimal solutions using classical and evolutionary generating methods. *European Journal of Operational Research (EJOR)*, 181(3):1630–1652, 2007.

[21] K. Sinha. Reliability-based multi-objective optimization for automotive crashworthiness and occupant safety. *Structural and Multidisciplinary Optimization*, 33:255–268, 2007.

[22] R. Srivastava and K. Deb. Bayesian reliability analysis under incomplete information using evolutionary algorithms. In *Simulated Evolution and Learning*, pages 435–444. Berlin, Heidelberg: Springer, 2010. Lecture Notes in Computer Science, 6457.

[23] R. Srivastava, K. Deb, and R. Tulsyan. An evolutionary algorithm based approach to design optimization using evidence theory. *Journal of Mechanical Design*, 135(8), 2013.

[24] K. C. Tan, E. F. Khor, and T. H. Lee. *Multiobjective Evolutionary Algorithms and Applications*. London, UK: Springer-Verlag, 2005.

[25] D. S. Todd and P. Sen. A multiple criteria genetic algorithm for containership loading. In *Proceedings of the Seventh International Conference on Genetic Algorithms*, pages 674–681, 1997.

[26] L. Xuebin. Multiobjective optimization and multiattribute decision making study of ship's principal parameters in conceptual design. *Journal of Ship Research*, 53(2):83–99, 2009.

APPENDIX

A. EVALUATION OF A DESIGN USING MCKESSEN'S MODEL

The following pseudo-code is used for evaluating a design, represented by three variables. If constraint violation is negative, the design is infeasible.

```
[f, Constr] = McKessen_ship_model(x)
{
 [DWT, Vknots, Beam] = x;
 LBP = 100.0; CB1 = 1.0; CB2 = 1.0; Ps = 0.0;
 i = 0 ;
 Condition =  0;
 while( i == 0 || Condition == 1)
 {
  LBP = LBP*pow((CB2/CB1), 1.0/3.0);
  Depth = 0.087 * LBP;
  Draft = 0.73 * Depth;
  FN_l = 0.51444*Vknots/sqrt(9.81*LBP);
  CB1 = 0.7+0.125*atan((23.0-100.0*FN_l)/4.0);
  W_Steel = 0.07 * LBP * Depth * Beam;
  W_Power = 0.25 * Ps;
  W_LightShip = W_Steel + W_Power;
  W_FullLoad = W_LightShip + DWT;
  Displacement = W_FullLoad / 1.025;
  Ps = 2.0 * pow(FN_l, 3.0) * W_FullLoad;
  CB2 = Displacement / LBP / Draft / Beam;
  if (CB1 < 0.99 * CB2 || CB1 > 1.01 * CB2)
    Condition = 1;
  else
    Condition = 0;
  i++;
 }
 COST_Acq = 1000.0*Ps+1000.0*W_LightShip;
 COST_Wages = 25.0 * 150000.0;
 COST_Fuel = 0.25 * Ps * 4800.0;
 COST_Operation = COST_Wages + COST_Fuel;
 AnnualCOST = COST_Operation+1.0/30.0*COST_Acq;
 TRANSPORT  = 4800.0 * Vknots * DWT;
 f = [AnnaulCOST, -TRANSPORT];
/* Constraint Evaluation */
 KG  = Depth / 2.0;
 KB  = Draft / 2.0;
 I_T = 0.5 * LBP * pow(Beam, 3.0) / 12.0;
 BM  = I_T / Displacement;
 GM  = KB + BM - KG;
 Constr = GM;
}
```

B. EVALUATION OF A DESIGN USING SEN-BULKER MODEL

The functional forms of $a(C_B)$ and $b(C_B)$ are given elsewhere [19]. A solution having positive value for all constraints is considered feasible. The allowable variable values are $190 \leq L \leq 500$ m, $10 \leq T \leq 27$ m, $12 \leq D \leq 51$ m, $0.63 \leq C_B \leq 0.75$, $22 \leq B \leq 75$ m, and $14 \leq V \leq 18$ Knots.

```
[f, Constr] = Sen-Bulker_ship_model(x)
{
 [L,T,D,C_B,B,V] = x;
 Displ = 1.025*L*B*T*C_B;
 P = Displ^(2/3)*V^3/(b(C_B)*V/(9.8065*L)^.5
     + a(C_B));
 Steel_mass = 0.0034*L^1.7*B^0.7*D^0.4*C_B^0.5;
 Outfit_mass = L^0.8*B^0.6*D^0.3*C_B^0.1;
 Machine_mass = 0.17*P^0.9;
 Dead_wt = Displ - Ship_mass;
 Daily_consmp = 0.2+0.19*P*0.024;
 Sea_days = 5000/(24*V);
 Fuel_carried = Daily_consmp*(Sea_days+5);
 Crew = 2*Dead_wt^0.5;
 Cargo_dw = Dead_wt-Fuel_carried-Crew;
 Port_days = 2*(Cargo_dw/8000 + 0.5);
 Ship_cost = 1.3*(2000*Steel_mass^0.85
            + 3500*Outfit_mass+2400*P^0.8);
 Running_cost= 40000*Dead_wt^0.3;
 Fuel_cost = 1.05*Daily_consmp*Sea_days*100;
 Port_cost = 6.3*Dead_wt^0.8;
 Voyage_cost = Fuel_cost + port_cost;
 RTPA = 350/(Sea_days + Port_days);
 Annual_cost = 0.2*Ship_cost+Running_cost
              + Voyage_cost*RTPA;
 Annual_cargo = Cargo_dw * RTPA;
 Light_ship_mass = Steel_mass + Outfit_mass
                  + Machine_mass;
 Transp_cost = Annual_cost/Annual_cargo;
 f = [Transp_cost, Light_ship_mass/10^4,
```

```
      -Annual_cargo/10^6];
/* Constraint Evaluation */
 GM = 0.53*T+(0.085*C_B-0.002)*B^2/(T*C_B)
      + 0.52*D+1;
 Constr(1)=L/B - 6; Constr(2)=15 - L/D;
 Constr(3) = 19 - L/T;
 Constr(4) = 0.45*Dead_wt^0.31 - T;
 Constr(5) = 0.7*D+0.7-T; Constr(6)=Dead_wt-3000;
 Constr(7) = 500000 - Dead_wt;
 Constr(8) = 0.32-V/(9.8065*L)^0.5;
 Constr(9) = GM - 0.07*B;
}
```