Optimal design of a helical coil support for dewars in fuel cell applications

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Abstract
Fuel cells are gaining popularity because of their efficient energy production without causing environmental pollution. Recently, DRDO has developed a fuel cell-based air-independent propulsion (AIP) system. In this system, the hydrogen is produced onboard while oxygen is carried in liquefied form (LOX) from the land in specially designed insulated storage vessels called dewars. Such vessels are needed because LOX has a low boiling point (NBP ~ 90 K) and heat of vaporization (~213 kJ/kg), due to which it boils off easily even when there is a small amount of heat inleak from the ambient. A typical dewar consists of two vessels separated by insulation. Support members are used to hold the two vessels together. Heat inleak through the supports and the insulation of the dewar causes the boiling of LOX. The vessels are subjected to dynamic loads during the voyage due to the filling and consumption of LOX. Therefore, the support system should be designed to withstand the dynamic loads experienced by the dewar. While the support system should have enough mechanical strength to withstand the loads it is subjected to, it should also restrict the heat inleak from the ambient to minimize the LOX boil-off. To meet this requirement, we need to optimize the support system design. Design optimization of support systems is especially critical in submarines to reduce the snorkeling frequency. Even though the dewars are available commercially for various applications, their design methodologies are not available in the open literature. Cylindrical rods are generally used as support members. In earlier studies, the authors have shown that helical coils give better thermal performance than tension rods as dewar supports. These two support systems involve different design criteria. It is important to evolve an optimal design of the support system to maximize the mechanical strength of the support while minimizing the heat inleak through the support. In this paper, we present a design methodology for optimizing helical support. We have proposed a modified optimization technique derived from the classical genetic algorithm (GA) for this purpose. The modification has been done by ensuring the design feasibility of the coil at each step of the algorithm. The proposed optimization technique has been tested on a LOX dewar, and an optimal design of the helical coil support has been obtained.

Keywords Fuel cell · Dewars · Liquid oxygen · Genetic algorithm · Optimization · Helical coil

Introduction
Submarines are important strategic and surveillance vehicles employed by navies of the world. Their missions require them to be underwater for long durations of time. Energy production for propulsion and running auxiliary systems while submerged is challenging. Most power sources require atmospheric oxygen to work and produce gases that need to be removed. Air is taken in tanks in the submarine to be utilized during underwater maneuvering. However, the submarine has to surface (snorkel) to refill the tank to maintain the amount of air in this tank. Snorkeling increases the chances of detection of the submarine by enemy anti-submarine warfare machines (Benedict 2005). Another challenge
is the disposal of the waste gases produced. Waste gases are generally hotter than seawater. Releasing these gases into the sea creates a thermal footprint of the submarine that can be detected by anti-submarine drones (Ya’ari 1997). Air-independent propulsion (AIP) systems have been developed for submarine applications due to these reasons (de-Troya et al. 2016). Two of the feasible AIP technologies are nuclear and fuel cell based. Nuclear energy sources have high reliability, high efficiency, and have very high energy density for the fuel mass carried. However, nuclear submarines pose dangers of nuclear radiation and leak. Disposal of used nuclear fuel from submarines is also challenging as they cause adverse effects on life and the environment. Fuel cell AIP systems are relatively safer compared to nuclear AIPs.

A typical fuel cell requires \( \text{O}_2 \) and \( \text{H}_2 \) to operate. For bulk transportation, oxygen, like many other gases such as natural gas and petroleum gas, is transported as liquid (liquid oxygen (LOX)) to reduce the storage volume for a unit mass of the species; in case of oxygen, a volume reduction of about 800 times is realized by transporting as LOX. Like LNG, LOX transport calls for specially designed vessels to suppress the easy boil-off of LOX because the storage temperature is much lower (~90 K at 1 atm) (Barron 1985) than the ambient temperature (~300 K). Efficient suppression of boil-off is necessitated to reduce the loss of oxygen and the hazards associated with the oxygen leakage and over pressurization of the storage vessel.

To circumvent the problem of over pressurization caused by boil-off gas, the gas is vented out of the vessel periodically. However, the venting of oxygen, used in fuel-cell powered submarines, would make the submarine vulnerable to easy detection by enemy reconnaissance sensors that follow the trail created by vented gas bubbles in the surrounding sea water. Thus, it is of strategic importance to design low boil-off LOX storage systems for fuel cell–powered submarines.

Furthermore, venting LOX is the loss of available oxidizer quantity for the fuel cell. Loss of oxidizer calls for frequent refilling of the LOX tank, thus reducing the mission time of the submarine. In order to tackle these issues, it is pertinent to develop LOX storage systems that prevent boil-off.

Since its introduction in 1898 (Foerg 2002), the dewar vessel has been the most popular cryogen storage medium. Dewar is essentially a double-walled container with the annular space filled with high-efficiency insulations such as MLI or evacuated powder insulation (Barron 1985). Figure 1 shows the construction of a typical dewar vessel.

The inner and outer vessels of the dewar are connected using support members. These support members hold the vessels in place under the action of various loads while resisting movements in all six degrees of freedom (UX, UY, UZ, ROTX, ROTY, ROTZ). Apart from these mechanical loads, thermal stresses are generated in the support members as the end fixtures prevent the free contraction of the supports during the cool-down phase of the dewar. Therefore, the usual practice is to pre-tense the support members during fabrication to neutralize the effects of thermal stresses.

For achieving the desired strength and easy welding of the supports, the material of construction (MoC) of the support members is taken same as that of the tanks. SS304/SS316 is used as MoC for cryogenic vessels like LOX tanks. This has much higher thermal conductivity (~six orders of magnitude more) than the insulation used in the tanks. Therefore, support members create a thermal short between the vessels, and thus leads to high heat inleak into the cryogen from the ambient. It has been stated that about 50% of heat inleak into a dewar is through the support members (Jacob et al. 1993). The magnitude of heat inleak depends on the dewar size and the type of insulation (Nitin et al. 2022).

An ineffective support system can nullify the effect of a good insulation system. Due to these reasons, the support members need to be designed for minimum heat inleak and maximum mechanical strength. Mechanical strength of different support systems is evaluated in terms of realized factor of safety (RFOS), which is the ratio of the yield strength of the MoC to the maximum stress generated in

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**Fig. 1** Construction of a typical dewar showing the major components. (1) Outer vessel, (2) inner vessel, (3) input/output vent, (4) support members. Black circles represent the support—dewar fixture locations.
the support. Slender cylindrical rods are generally used as dewar supports. Cylindrical rods withstand greater tensile loads than other cross sections of the same area (Barron 1985). Straps and struts as dewar supports have been studied and designed for space-borne dewars (Kittel 1993; Reed and Golda 1997). They are highly specialized for aeronautical systems and cannot be applied for submarines. Concentric cylinders, posts, stacked plates, and helical coils are some other reported dewar supports. Apart from these, a few patented designs of dewar supports are available (Hibl et al. 1975; Silver et al. 1985). These designs are application-specific and difficult to fabricate. In addition, the steps involved in their design are not obvious. To the best of the authors’ knowledge, a comprehensive design methodology of dewar support is not available in the open literature.

Studies on helical coils as dewar supports were recently reported (Virdi et al. 2019; Nitin et al. 2021). In these studies, comparisons were made between cylindrical rod support and helical support in their mechanical and thermal performances. It was found that the latter had superior thermal and inferior mechanical strength compared to the former.

The performances of the helical coil are functions of its wire diameter, coil diameter, and pitch. Several helical coils can be generated by varying these parameters. An optimized set of these dimensions are to be found to design efficient support. Also, the dimensions of the supports are dependent on the dimensions of the dewar itself (inner and outer vessel diameters and inner vessel length). This dependence has not been reported in the literature. These have been derived in the present work. The present work optimizes the design of helical coils used as dewar supports to maximize the mechanical strength and minimize the heat inleak through the supports.

The optimization problem is multi-variate and multi-objective. Also, as all the combinations of the variables need not generate coils, the objective functions are discontinuous. Traditional optimization techniques like the steepest descent method (Fliege and Svaiter 2000) and conjugate descent method (Dai et al. 2003) are gradient finding methods. These methods cannot be employed in this problem as they have a probability of getting stuck in a local optimum and cannot be used to optimize discontinuous functions. The random walk method (Bertsimas and Vempala 2004) is a hit-and-trial method that can be used on discontinuous functions; however, the ability of the random walk method to find the optima depends on the starting point and the stride size. There is no guarantee that a random walk method will converge to a global maxima even after running the procedure for a long time. Exhaustive search optimization (Krumme and Ackley 1982) searches for the optima by computing the function value at all points in the parameter space. Although the exhaustive search method is guaranteed to find the global optima, the method takes long time when the function is complicated or when the parameter space is large. Non-traditional optimization strategies are developed to overcome the limitations of the said methods. Genetic algorithms (GA) (Deb 1998), simulated annealing (SA) (Kirkpatrick and Gelatt 1983), ant colony optimization (ACO) (Dorigo and Caro 1999), particle swarm optimization (PSO) (Polli et al. 2007), etc. are some examples of non-traditional optimization algorithms. These algorithms are motivated by the behavior of biological or physical systems. GA, ACO, and PSO are population-based optimization techniques where after each iteration, the population moves closer to the optima. SA performs optimization by mimicking the cooling process of a metal body where the body tries to attain the minimum energy state. Although GA and SA can handle multi-variate optimization of discontinuous functions, unlike traditional algorithms, GA and SA are computationally expensive and take a long time to converge. Parallel computing can reduce the time taken by these algorithms to find the optima. Implementing parallel computing in GA is relatively simpler compared to SA. In this work, we have employed GA as the optimization tool due to these reasons.

GA has been used to find optimal set of dimensional/operational parameters in mechanical design problems (Subramanian et al. 2013; Li et al. 2005; Alkhatib et al. 2004), chemical processes (Yu et al. 2000, Wang et al 1996), thermal engineering problems (Mohebbi et al. 2008; Ahmadzadeh et al. 2017; Saha et al. 2018), etc. In this paper, we applied GA to optimize the design of a support member of a dewar.

Modelling

Optimization studies need a knowledge of the system behavior. Therefore, the mechanical and thermal behavior of the support system has been modeled to arrive at the objective functions for optimization.

Mechanical performance model

For modeling the mechanical performance of the helical coil supports, their RFOS is found. The model assumptions are as follows:

1. The MoC of the support is homogeneous and isotropic; this is true for the considered MoC (SS304) (Sadd 2009).
2. Supports loaded in tension allow less heat inleak than those loaded in compression (Barron 1985). Hence, we assume that the supports are loaded in tension in this work.
3. Since symmetric structures are more stable than un
symmetric structures, designs usually enforce symme-
try. This work assumes that load is equally distributed
amongst the supports to increase stability.
4. The cooldown period of a dewar is negligible compared
to the operation time of the dewar. This work assumes
that the dewar is completely cooled down.
5. The weight of the inner tank is about four orders of mag-
nitude less than the weight of the cryogen and hence the
weight of the inner tank is neglected.

The free-body diagram of coil support, under the applica-
tion of loads, is shown in Fig. 2

As per assumption (4), the thermal stresses generated in
the support are completely compensated by their pretension.
The mechanical load and the stress thus generated are elabo-
rated in the following sections.

**Mechanical load**

As per assumption (5), the dynamic load on the support is
dictated by the weight of the cryogen in the tank (Barron
1985; Nitin and Sandilya 2018), given by:

\[ P_{\text{total}} = 8P_{\text{static}} = 8m_{\text{liquid}}g = 8\rho_{\text{LOX}}V_{\text{liquid}}g \]  

By assumption (3), the mechanical load acting on an individual support is,

\[ P = \frac{P_{\text{total}}}{n} \]  

where \( n \) is the number of support members.

**Mechanical stress in helical coil support**

A load acting on the helical coil in the direction of the axis
of the coil generates two types of stresses on the coil: (1)
tensile stress \( (\sigma) \) acting along the wire axis of the coil and
(2) shear stress \( (\tau) \) acting perpendicular to the axis of the
wire axis. Tensile and shear stresses are found as (Shigley et al. 2008),

\[ \sigma = \frac{8Pd_c}{\pi d_w^2} \]  

and

\[ \tau = \frac{8Pd_c}{\pi d_w^2} \left( \sin \left( \tan^{-1} \left( \frac{p}{2\pi d_c} \right) \right) + 1 \right) \]  

The coil support fails when either of the stresses exceeds
the yield strengths of the material. The RFOS is thus derived as,

\[ \text{RFOS} = \min \left[ \frac{\sigma_{ys}}{\sigma}, \frac{\tau_{ys}}{\tau} \right] \]

**Thermal performance model**

The thermal performance of the supports is a measure of the
heat ingress the support allows through it. To model this, we
find the heat transfer occurring through the supports (Fig. 3). The following assumptions are made:

1. The MoC of the support is homogeneous and isotropic;
this is true for the considered MoC (SS304).
2. Heat transfer is steady state, i.e., the dewar has cooled
down.
3. Heat transfer through the support is predominantly 1-D
along the axis of the support wire; this is true as the con-
sidered MoC (SS304) of the support has high thermal
conductivity, and the length of the support wire in the
axial is more than that in the radial direction.
4. The liquid cryogen is saturated at the ullage pressure to
design the support system for maximum possible liquid
boil off loss.

![Figure 2](image-url)  

**Fig. 2** Free body diagrams of a cylindrical rod support and a coil sup-
port under the application of load \( P \). \( d_c \) is the wire diameter, \( d_w \) is the
coil diameter, and \( l \) is the length of the support. \( T_h \) is the temperature
of the outer vessel and \( T_c \) is the cryogen temperature. (1) and (2) are
the faces of the support in contact with the outer and inner vessels, respectively.
5. The ullage pressure is constant.

The temperature distribution in the support is found by solving the steady state 1-D energy balance equation given by,

\[
\frac{\partial}{\partial x} \left[ k \frac{\partial T}{\partial x} \right] = 0
\]  

(6)

Subjected to the constraints

At \( x = 0; T = T_H \) and at \( x = l_{\text{heat}}; T = T_C \)

The heat inleak through the support is obtained by solving Fourier’s law of conduction.

\[
\dot{Q}_{\text{support}} = \frac{k \pi d^2}{4} \frac{dT}{dx}
\]  

(7)

For most materials used at cryogenic temperature, thermal conductivity is a function of temperature (He et al. 2019). The variation of thermal conductivity has been incorporated in the model. Discreet values of thermal conductivities at cryogenic temperatures are tabulated in the literature (Bradley and Radebaugh 2013). These values are regressed as (Nitin et al 2020),

\[
k(T) = A_1 T + A_2
\]  

(8)

To determine the boil-off rate of the stored LOX, mass and energy conservation are applied within the inner vessel. The control volume considered is shown in Fig. 4.

Mass balance applied to the CV is written as,

\[
\frac{dm_{\text{liquid}}}{dt} = \dot{m}_{\text{boil-off}}
\]  

(9)

The mass remaining in the CV at any time can be computed subjecting Eq. 9 to,

At \( t = 0, m_{\text{liquid}} = m_{\text{liquid},0} \)

According to assumptions (4) and (5), the energy balance equation is written as,

\[
\dot{m}_{\text{boil-off}} = \frac{\dot{Q}_{\text{boil-off}}}{h_{fg}}
\]  

(10)

The rate of liquid mass boil-off is found from,

\[
\dot{m}_{\text{boil-off}} = \frac{\dot{Q}_{\text{boil-off}}}{h_{fg}}
\]  

(11)

It should be noted that the boil-off calculation involves the consideration of many types of heat interactions due to the liquid circulation, thermal stratification in the liquid and the ullage, sloshing, heat inleak, etc. However, the study on these heat interactions has to be dealt with separately and hence not included in this paper.
Dependence of support dimensions on dewar size

Support members can be attached to the inner and outer vessels at any location. However, to increase the thermal length between the vessels, the supports are attached diagonally in the annular space of the dewar. Figure 5 shows the relationship between the length of the support and the dimensions of the dewar.

The axial length of the support is derived as,

$$ AC^2 = AB^2 + BC^2 $$

$$ BC = \sqrt{AC^2 - AB^2} $$

$$ l_2 = \sqrt{R_o^2 - R_i^2} $$

$$ \beta = \tan^{-1}\left(\frac{R_i}{R_o}\right) $$

In Δe BCD

$$ \frac{l_1}{l_2} = \cos(\beta) $$

$$ l_1 = l_2 \cos\left(\tan^{-1}\left(\frac{R_i}{R_o}\right)\right) $$

$$ l = L^2 + l_1^2 $$

$$ l = \sqrt{L^2 + \left(\sqrt{R_o^2 - R_i^2} \cos\left(\tan^{-1}\left(\frac{R_i}{R_o}\right)\right)\right)^2} $$

A heat transfer length of the support is the length of the stretched coil given by Lingaiah (2003),

$$ l_{heat} = \pi d_c \left(\frac{l - d_w}{p}\right) $$

Objective function

As mentioned before, the optimal coil has maximum RFOS and minimum $\dot{Q}_{support}$. For this, Eq. 5 is to be maximized, and Eq. 7 is to be minimized. GA, by definition, is a maximizing technique (Pratihar 2007). Minimizing Eq. 7 has to be reframed into a maximization problem for the implementation of GA. Equation 13 shows the conversion strategy used in the present work,

$$ \dot{Q}_{support}^* = \frac{1}{1 + \dot{Q}_{support}^2} $$

Since the optimization problem is multi-objective, a hybrid fitness function is formulated using linear scalarization as,

$$ f(d_w, d_c, P) = w_1 RFOS + w_2 \dot{Q}_{support}^* $$

f represents the hybrid fitness function which includes the combined mechanical and thermal performance of the supports. The weights $w_1$ and $w_2$ define the contribution of each of these performances on the hybrid fitness function.

Variables and constraints

Wire diameter of the coil ($d_w$)

The minimum wire diameter is that which is just sufficient to sustain the loads if the support was a cylindrical rod. This diameter is found as,

$$ \min(d_w) = \sqrt{\frac{4P}{\pi \sigma_{ys}}} $$
The maximum wire diameter is that which can execute at least two turns within the length of the support. This diameter is found as,
\[ \text{max}(d_w) = l - 2p \] (16)

**Coil diameter \((d_c)\)**

The fusing of the wires of the coil reduces the thermal distance between the ends of the support. The minimum coil diameter is that which prevents the radial fusing of the wires. This coil diameter is found as,
\[ \text{min}(d_c) = 2d_w \] (17)

The maximum coil diameter is the radius of the annular space.
\[ \text{max}(d_c) = \Delta R \] (18)

**Pitch \((p)\)**

To prevent the axial fusing of the wires of the coil, the minimum pitch is twice the diameter of the wire.
\[ \text{min}(p) = d_w \] (19)

The maximum pitch is that which executes two turns of the coil wire. This pitch is found as,
\[ \text{max}(p) = \frac{l - d_w}{2} \] (20)

The constraints are summarized in Table 1.

### Encoding/mapping the variables into chromosomes

In GA, a set of variables is called an individual. Each individual is represented by a chromosome. The chromosome contains genes whose count corresponds to the number of variables. In the present problem, a chromosome contains three genes as there are three variables. Binary encoding (Meng et al. 1999) is employed to encode/map the variable value into the gene; binary encoding technique was used as computer systems handle Boolean operations faster than floating-point operations. In binary encoding, the gene contains a string of binary bits whose value represents the value of the corresponding variable. The length of the binary string is decided based on the resolution required for the variables. In order to achieve a resolution of at least 1000 for each of the variables, a 10-bit binary encoding (resolution of 1024) was used for each gene. Equation 21 gives the formula for the conversion of the binary strings to corresponding meaningful real values of the variables.
\[ x = x_{\text{min}} + \frac{x_{\text{max}} - x_{\text{min}}}{2^N - 1} \sum_{i=0}^{N} b_i 2^i \] (21)

where \(x\) is the real value of the variable, \(x_{\text{max}}\) and \(x_{\text{min}}\) are the maximum and minimum values of the variable, \(N\) is the number of binary bits representing the variable, and \(b_i\) is the \(i\)th bit of the binary string.

At the start of the algorithm, genes are populated with random binary bits. We used a time seeded positive random number generator to generate random binary bits. Once the binary strings are generated for each of the genes, the genes are stacked one after the other to form the chromosome of the individual. Figure 6 shows an individual chromosome encoded using this procedure.

### Population

A group of individual chromosomes is known as the population. \(N_{\text{pop}}\) represents the number of individuals in a population. Usually, in GA, the variable constraints are fixed numerical values with no dependence on the other variable values. However, as seen from Table 1, this is not true in the present study. One needs to ensure that only the feasible individuals are allowed to become the optimized value. Infeasible individuals can be removed by imposing a penalty on their fitness values. This imposition happens after the initial generation is populated. There is a chance that the initial population may contain several infeasible individuals. These individuals would be rejected based on their fitness value, thus producing no undesirable effect on the solution. However, as the number of such infeasible individuals in the initial population increases, there is a chance that only a limited number of feasible individuals propagates into subsequent generations. Reduction in the number of feasible individuals lowers the chances of the GA converging towards the actual global optima. Global maxima in such cases may be reached by increasing the probability of mutation. However, increasing the probability of mutation may reduce the algorithm’s efficiency and render it similar to a random search technique.

In the present work, a novel method to overcome the issue under study has been employed. While populating the initial

| Variables | Minimum value | Maximum value |
|-----------|---------------|---------------|
| \(d_w\)   | \(\sqrt{(4p)/(\pi\sigma_w)}\) | \(l - 2p\)   |
| \(d_c\)   | \(2d_w\)      | \(\Delta R\)  |
| \(p\)     | \(d_c\)       | \((l - d_w)/2\) |
generation, the feasibility of the variables is checked for each individual, and the infeasible individuals are removed. This method ensures that the number of individuals in the initial population matches the desirable population size.

**Selection**

GA is an iterative process, and each iteration is called a generation. As per the theory of evolution, the succeeding generations have better average fitness than their parents. The fitness improves because the desirable traits of the parents are handed over to their offspring. Only certain “eligible” parents are allowed to mate and reproduce to ensure this. Eligibility is based on the fitness of the parents. Choosing the eligible parents is called selection. GA has several selection methods like tournament selection, probability selection (or roulette wheel selection), ranking selection, and elitism (Lim and Haron 2013). Tournament selection is used in this work as this method is computationally faster than the other methods. A fixed number of parent chromosomes are selected from the population in tournament selection. The fittest parent from this selection is sent to the mating pool; this process is called a tournament. In order to keep the number of individuals in the generations the same, many tournaments are conducted.

**Reproduction**

Reproduction is the process by which two parent chromosomes in the mating pool combine to produce offspring. The crossover operator performs reproduction. The crossover operator slices both the parents’ chromosomes and stitches one parent’s chromosome with the complementary chromosome of the other parent. Thus, one crossover produces two offspring. A two-point crossover (Hongze et al. 2000) operator acting at chromosome length locations 10 and 20 is employed in this work. The crossover may yield a chromosome whose offspring are infeasible. These offspring need to be removed. In this work, offspring are checked for their feasibility post crossover. If they are feasible, then crossover takes place; else, the parents continue to the next generation as themselves. It is also possible that the feasible offspring produced by crossover have less fitness than their parents. In order to prevent any undesirable effect such crossover might have on the algorithm, some parents continue to proceed to the next generation as themselves. Whether parents undergo crossover or not is made based on a probability constant ($P_c$).

**Mutation**

In natural evolution, it can be observed that certain offspring have characteristics that belong to neither of their parents. Deviation in the characters of the individuals occurs due to “17.” In any optimization procedure, there is a chance that the solution proceeds towards a local optimum. In GA, this is avoided by inducing an abrupt change in the individual’s genome. In the present study, mutation may produce infeasible offspring. The feasibility of an individual is checked post mutation. If the individual is feasible, mutation proceeds; if the individual is infeasible, the mutation is reversed. Too much mutation reduces the efficiency of GA by making it proceed similar to a random walk method. In order to prevent this, the decision if an individual will be mutated or not is decided based on the mutation probability constant ($P_m$).

Evolution proceeds until the maximum fitness of individuals in successive generations converges. After convergence, the individual having maximum fitness in the last generation will have the optimal variables. However, there is still a small chance that the GA might have stuck at local maxima. In order to add an extra layer of protection against this, the mutation operator acts on a few randomly selected individuals ($N_{mut}$) of the final generation. Suppose these mutated
individuals have fitness less than the maximum fitness value. In that case, the maxima found from the previous step is taken as the final optima. Suppose any of these individuals have fitness greater than the maximum fitness. In that case, multiple copies of the mutated individuals are added to the population. The complete algorithm of the process is shown in Fig. 7.

**Selection of the GA parameters**

$P_c$ and $P_m$ should be carefully chosen so that the algorithm converges faster. In this work, the algorithm is run on a small pilot population, varying one of the probabilities keeping the other constant. That value of the probability that gives the maximum fitness is chosen as the optimal probability value. The algorithm is run on the test population using these optimal values of probabilities.

**Results and discussion**

To illustrate the proposed optimization method, we considered a hypothetical cylindrical dewar of MoC SS 304. The dewar is filled with saturated LOX at 1 atm. In order to restrict all the six degrees of freedom (UX, UY, UZ, ROTX, ROTY, ROTZ), six supports are employed (Barron 1985). The dimensions of the considered vessels are summarized in Table 2.

| Dimension                  | Value |
|---------------------------|-------|
| Radius of the outer vessel | $R_o$ 850 mm |
| Radius of the inner vessel | $R_i$ 500 mm |
| Length of the inner vessel | $L$ 2 m |
| Number of supports        | $n$ 6 |

**Table 2** Vessel dimension of the hypothetical LOX vessel

Fig. 7 Flow chart of the amended GA used to find the optimum coil dimensions
The total load acting on the support system is found as per Eq. 1,

\[ P_{\text{total}} = 8\rho_{\text{LOX}} \pi R_i^2 L_g = 140.8 \text{ kN} \]

The load acting on a single support member, \( P \) is found using Eq. 2.

\[ P = \frac{140.8}{6} \text{ kN} = 23.5 \text{ kN} \]

The length of the support is obtained as,

\[ l = 2086 \text{ mm} \]

The temperature of LOX in the vessel is 90 K. The ambient temperature is taken as 300 K. The constants used for thermal conductivity evaluation as per Eq. 8 are given in Table 3.

An in-house C++ program was developed to implement the optimization procedure. GA parameters used in this work are tabulated in Table 4. The plots showing the variation of fitness for various values of \( P_c \) and \( P_m \) are shown in Fig. 8 and Fig. 9, respectively.

After convergence of the algorithm, the coil geometry variables are obtained as \( d_w = 118.5 \text{ mm} \), \( d_c = 298 \text{ mm} \), and \( p = 123.5 \text{ mm} \). A CAD geometry of the optimized coil is shown in Fig. 10.

We now check the closeness of the optimized variables to the limits of the variables.

According to Eq. 17 and Eq. 18, the lower and upper limits of \( d_c \) are,

\[ \min(d_c) = 237 \text{ mm} : \max(d_c) = 350 \text{ mm} \]

The optimized value of \( d_c \) is closer to the lower limit (46%) of the variable.

According to Eq. 15 and Eq. 16, the lower and upper limits of \( d_w \) are,

\[ \min(d_w) = 11.8 \text{ mm} : \max(d_w) = 1838 \text{ mm} \]

The optimized value of \( d_w \) is closer to the lower limit (6%) of the variable.

According to Eq. 19 and Eq. 20, the lower and upper limits of \( p \) are,

\[ \min(p) = 118.5 \text{ mm} : \max(p) = 983.2 \text{ mm} \]

The optimized value of \( p \) is closer to the lower limit (0.6%) of the variable.

The closeness of the variables to the lower limit suggests that the optimized coil tends towards a closed coil tension spring. However, a closed coil tension spring cannot be used as dewar supports as the contact between the coils would create a thermal short between the vessels. Jacketed closed helical coils can be effectively employed as dewar supports.

| Material | \( A_1 \) | \( A_2 \) |
|----------|--------|--------|
| SS 304   | 0.0328 | 5.8436 |

| Parameter | Value |
|-----------|-------|
| \( N_{\text{pop}} \) | 10,000 |
| \( P_c \) | 0.7 |
| \( P_m \) | 0.02 |

Fig. 8 Fitness corresponding to various values of \( P_c \)

Fig. 9 Fitness corresponding to various values of \( P_m \)
Performance comparison of the presented and existing support designs

To explore the improvement in the mechanical and thermal performances of supports through design optimization, we compared these performances of the support developed in this study with those of the existing support (straight cylindrical rod). For this purpose, we determined the heat inleak, boil-off rate, and RFOS of the dewar specified in Table 2, for the two cases. The diameter of the straight cylindrical rod was taken same as the wire diameter obtained for the optimized coil support. The comparison is tabulated in Table 5, which shows that about 86% reduction in the heat inleak is obtained through optimization; the boil-off rate will also be reduced to the same extent if the liquid is taken to be saturated. On the other hand, the RFOS is considerably less for the optimized support; since the RFOS is much higher than unity in both the cases in both the cases, both the support structures have high mechanical integrity but the optimized structure can bring down the mass or payload of the system by about 88% and thus a significant reduction in the overall cost of the system.

Conclusions

In this work, we optimized a helical coil dewar support design. A modified version of the classical GA was employed as the optimization tool. Feasibility of the coil and global optima were ensured in the optimization process. Some of the salient contributions of this work are as follows:

1. Relationship between the support length and the dewar dimensions was derived for the first time.
2. Interrelationship between the dimensions of the coil has been derived in the work.
3. A multi-objective multivariable fitness function was developed to optimize dewar support design.

In future the, authors intend to extend this analysis to the entire support system.

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Table 5 Performances of the optimized helical coil support

| Support                | Heat inleak (W) | RFOS |
|------------------------|-----------------|------|
| Optimized helical coil | 1.9             | 11.6 |
| Straight cylindrical   | 13.6            | 96.7 |

Fig. 10 CAD drawing of the optimized coil geometry
