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REGULAR ARTICLE

Development of Novel Optimization Technique for Surface Duct Estimation on Thin Films

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Surface duct is a well-observed occurrence in the atmospheric airspace whereby a thin layer of airspace is formed closer to the surface, hence advancing the propagation range of electromagnetic signals. This ducting effect can improve radar and radio signal transmission, which affects communication and surveillance applications. The environmental factors at the site could affect the formation of the duct and the reliance on a specific set of modelling assumptions made with the Monterey-Miami Parabolic Equation (MMPE) approach of the ducting system. To estimate the surface ducts more effectively, the Artificial Fish Swarm Driven Dynamic Seagull Optimization (AFS-DSO) technique is employed in this study. Using several iterations, the study investigates propagation loss, objective function, convergence rate, and clutter power modelling as electromagnetic wave propagation attributes. The efficiency of the proposed AFS-DSO is found to be higher than the conventional technique of Dynamic Seagull Optimization (DSO). The results show the effectiveness of the improvement compared to the baseline using hybrid optimization algorithms, which can improve estimates of surface ducts for radar and thin film applications.

Keywords: Surface duct, Electromagnetic propagation, Monterey-Miami Parabolic Equation (MMPE), Artificial Fish Swarm Driven Dynamic Seagull Optimization (AFS-DSO), Radar systems.

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1. INTRODUCTION

Thin films are defined as layers of material that are the arrangement of a few nanometres (nm) to a few micrometres (mm) in thickness. It has a common feature of contemporary technologies in optics and electronics as protective coatings. Some of the useful features include reflectivity and electrical conductivity that are suitable for applications such as semiconductors, solar cells, and sensors. Therefore, to improve the performance level of thin films, it is necessary to examine their surface properties because slight deviation would lead to deprived performance. It helps to predict the surface ducts, a stochastic process that affects the wave behaviours in thin-film surfaces [1].

Subordinate surface ducts occur when waves, including electromagnetic or acoustic waves channelled, are close to the surface by a condition in the environment or the materials surrounding them. In thin films, the confinement could change the frequency at which signals could be transmitted and these dependencies directly impact the effectiveness of the devices. Correct estimation of these ducts is important to improve the propagation of these waves and minimize interferences in the effective usage of energy. However, due to the complex dependency of film properties and environmental parameters, the estimation of surface duct remains a problem among examiners [2].

The classical methods that are used to estimate surface ducts typically involve the use of approximation formulas, which fail to address the nonlinearity. Therefore, these methods could give false predictions which decrease the applications of thin film. Subsequently, surface-wave interactions involve multiple parameters and use new strategies to manage various parameters. To address these challenges, it has an efficient technique to improve

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the surface duct estimation for thin films [3].

The technical decision-making processes require optimization methods to reduce the level of errors and introduce higher levels of efficiency in the solutions implemented. In surface duct estimation, optimization helps in the identification of a parameter range to improve the efficiency of predictive models. Standard approaches have problems with local optimization and get stuck at local minima. To analyze these shortcomings, it presents a new and more efficient optimization algorithm that could adequately capture the dynamics of surface ducts [4-5].

The aim of the study is to create a new optimization procedure to determine the surface duct configurations on thin film, improving the liquid hold-up and flow capabilities. It is important to enhance performance indicators using more sophisticated algorithms and helps in application in fluid dynamics and material science [6-7].

2. RELATED WORKS

High performance and dependability attained by bulk niobium-based superconducting radio frequency (SRF) systems were examined in [8-9]. The materials and more sophisticated surfaces were required for the next generation of particle accelerators. By implementing the performance beyond superconductors, the community was creating next-generation thin-film-based cavities. The coated cavities for cost savings and thermal stability. It created cavities coated with materials for higher temperatures and fields.

The coatings of a thin film with certain characteristics arranged on a substrate to create new materials as semiconductors were investigated by [10]. The qualities of clean production procedures were essential. Purity and conformance were essential, and contaminants were removed by operating at an extremely high vacuum. For analysis or characterization, traditional techniques such as Raman analysis, as well as profilometry were used. The growth of an alloy of metal nitride was used to demonstrate initial evidence of performance.

The surfaces and heat flux in test engines were determined, while their adaptation to stable facilities presented difficulties. To handle gauge degradation over prolonged runtimes, [11] proposed remedies, including a nanotechnology technique and a novel calibrating technique. Impulse responsiveness technique for steady-duration facilities was included. It has the dissimilarities of new gauges made with contemporary nanotechnology methodologies for continual turbine test facilities with traditional heat flux gauges intended for short-duration capabilities.

In a duct containing a 10:1 ignition ratio, the [12] evaluated the destructive effects of biogas. The results of the experiment included an elemental material and a methane percentage that has distinct peak pressures as a result of an explosion, maximum flaming area, and film breakdown. The combination of the methanol percentage with film thickness generated a pressure gradient pattern. Torrent temperature was more affected by the film thickness than by the methane fraction. The study found that although film thickness had a significant effect on flame front velocity, it had a bigger effect on explosion pressure.

In this study [13], a nonintrusive X-ray determining technique for recreating the thickness pattern of thin liquid coatings in stable gas-liquid circular pipe motion was presented. Low fluid loading, circular flows, and different surface gases and liquid speeds have been utilized in the experiments. The technique could be used in circumstances where film volume predominates over droplet volume and was very sensitive.

3. FORWARD PROPAGATION MODEL

3.1 Propagation Equation Model

In this paper, MMPE parabolic equation to obtain the waves of the surface duct. The time-harmonic acoustical field is first represented in a cylinder coordinate system $(q\ , y,\ \varphi)$ by Equation (1).

$$O(q,y,\varphi,s) = o(q,y,\varphi)f^{-j\omega s} \tag{1}$$

The Helmholtz equation is obtained by substituting into the wave's equations using coordinates of a cylinder Equation (2).

$$\frac{1}{q}\frac{\partial}{\partial \mathrm{q}}\left(q\frac{\partial o}{\partial \mathrm{q}}\right) + \frac{1}{q^2}\frac{\partial^2 o}{\partial \mathrm{y}^2} + l_0^2 m^2(q,y,\varphi)o = -4\pi O_0 \delta(\dot{w} - \dot{w}_T) \tag{2}$$

Where is $l_0 = \frac{\omega}{d_0}$ the reference wavenumber and the sound speed of the surface duct indices of refraction.

$$\delta(\dot{w}) = \frac{1}{2\pi q}\delta(y - y_T)\delta(q) \tag{3}$$

The pressure magnitude with the reference wavenumber distances is a function of an individual source $q_0, y = y_t$ at dimensions equal to the source level O and defined as the pressure amplitude at the reference distance of q was obtained in Equation (3) is the Dirac-delta function defining the point source contribution. To reduce the Helmholtz equation's expression by taking account of the cylindrical dispersion that controls propagation, we define it in Equation (4).

$$o(q,y) = \frac{1}{\sqrt{q}}v(q,y) \tag{4}$$

Substituting the Equation (4) into Equation (3) and deriving Equation (5)

$$\frac{\partial^2 v}{\partial \mathrm{q}^2} + \frac{1}{q^2}\frac{\partial^2 v}{\partial \varphi^2} + \frac{\partial^2 v}{\partial \mathrm{y}^2} + l_0^2\left(m^2 + \frac{1}{4 l_0^2 q^2}\right)v = 0 \tag{5}$$

In the solution, the last term from this equation is frequently ignored and falls off thus. This equation's second term is typically tiny and provides azimuthal coupling between various radials. A common phrase for this term's neglect is the uncoupled azimuth (UNCA) approximation. For the remaining development, this stage allows complete three-dimensional (3D) computations. The operator notation can be used for the remaining factor of Helmholtz calculation Equations (6-9).

$$O_{op} = \frac{\partial}{\partial \mathrm{q}} \tag{6}$$

$$R_{op} = (\mu + \varepsilon + u + 1)^{123..n} \tag{7}$$

$$\varepsilon = m^2 - 1, \mu = \frac{1}{l_0^2}\frac{\partial^2}{\partial \mathrm{y}^2}, and\ u = \frac{1}{l_0^2 q^2}\frac{\partial^2}{\partial \varphi^2} \tag{8}$$

$$\left(O_{op}^2 + l_0^2 R_{op}^2\right)v = 0 \tag{9}$$

The outward propagation field is properly factorized by defining Equation (10).

$$v = R_{op}^{-\frac{1}{2}}\Psi \tag{10}$$

For several causes, including conserving power and the right initial state of the beginning field, it is crucial to incorporate the R_{po} variable, a first-order estimation, in Equation (11).

$$O_{op}\Psi = jl_0 R_{op}\Psi \tag{11}$$

Suppose that the commutator is very small, which suggests that the environment has little range dependency in Equation (12).

$$-jl_0^{-1}\frac{\partial \Psi}{\partial \mathrm{q}} = R_{op}\Psi \tag{12}$$

In reality, the commutator is precisely zero for layering the medium.

3.2 Propagation Loss

It also plays a critical role in estimating surface ducts on thin films that determine wave behaviour and performance. The total propagation loss K_o is calculated in Equation (13).

$$K_O = 10\ log_{10}\left(\frac{P_{transmitted}}{P_{received}}\right) + K_{surface} + K_{interface} \tag{13}$$

Where $K_{surface}$ examines variations in the surface characteristics. $K_{interface}$ Stands for reflection losses between film layers. Surface loss is modelled as represented in Equation (14).

$$K_{surface} = \alpha . e^2 . c \tag{14}$$

Where α is the surface loss coefficient, e is the frequency and c is the film thickness. Interface loss is given in Equation (15).

$$K_{interface} = Q.\left(\frac{m_1 - m_2}{m_1 + m_2}\right)^2 \tag{15}$$

Where m_1 and m_2 are the refractive indices of two layers When the first layer is thinner than the second layer, by further refining these parameters, the accuracy of estimation $K_{interface}$ of surface ducts is improved.

4. ARTIFICIAL FISH SWARM DRIVEN DYNAMIC SEAGULL OPTIMIZATION (AFS-DSO)

4.1 Dynamic Seagull Optimization Algorithm (DSO)

The DSO method has the benefits of fast integration, low cost of computation, and the ability to solve massively restricted problems. It has significant benefits over other algorithms for optimization. The general optimization search technique of DSO is linear. Because of the linear search method, DSO's extensive search capabilities cannot be fully leveraged. To increase the algorithm's rapidity and precision, we give a nonlinear searching control calculation, as illustrated in Equation (16) that can concentrate on the seagull groups' exploration process phase.

$$B = e_d\ X \frac{1}{f^{4.\left(\frac{s}{Max_{iteration}}\right)^4}} \tag{16}$$

Where f represents the base of the natural algorithm.

Flowchart of DSO starts with the initialization of parameters, including the maximum number of iterations and population size. The modification of the seagull population is followed by the calculation of fitness values for each seagull. The algorithm then updates the seagulls' migration and attack positions based on fitness evaluations. A nonlinear search strategy is pursued to focus the exploration phase so that it will seek an appropriate way to the solution space. This process is repeated until the maximum number of iterations is reached, ending with the identification of the most preferred solution.

4.2 Artificial Fish Swarm Optimization (AFS)

The AFS is an optimization algorithm that simulates the natural behavior of fish. In the same way, AFSA determines the following fish activities: swarming, following, and searching for food; it can also map out solution spaces that are complex to get global optimum solutions. It combines the ideas of swarm intelligence with artificial intelligence (AI) so that artificial fish (AF) can swim and search for the solution to the problems in the given field dynamically.

5. RESULTS AND DISCUSSIONS

5.1 Comparative Analysis

Table 1 presents the comparison of propagation loss (in dB) against distance (in Km) for two optimization methods: The innovative procedures of the DSO [18] and the AFS-DSO are introduced. The distance between the transmitter and receiver increases, and both DSO and AFS-DSO depict an increase in the propagation loss for the adopted transmission media. However, the AFS-DSO has a considerably lower propagation loss than DSO at all distances, which indicates better performance in terms of efficiency in propagation of signal. The increase in correctness of surface duct estimation implies that the AFS-DSO method optimizes the propagation characteristics of thin films.

Table 1 – Numerical values of propagation loss

Distance (Km)	Propagation Loss (dB)	
	DSO [18]	AFS-DSO [Proposed]
10	15	12.5
20	18	15
30	20.5	17
40	23	19
50	25.5	21.5
60	27	23
70	28.5	24.5
80	30	26
90	31.5	27.5
100	33	29

Fig. 1 of DSO and AFS-DSO shows that propagation loss represents different performance characteristics under different circumstances. The following graph shows the distribution of propagation loss for both techniques over distance. DSO usually indicates a higher amount of loss because of less flexible frequency selection, while AFS-DSO shows enhanced signal consideration and a reduced amount of loss in turbulent circumstances. The graph shows that AFS-DSO is a better solution for the propagation problem, which improves the quality of the link.

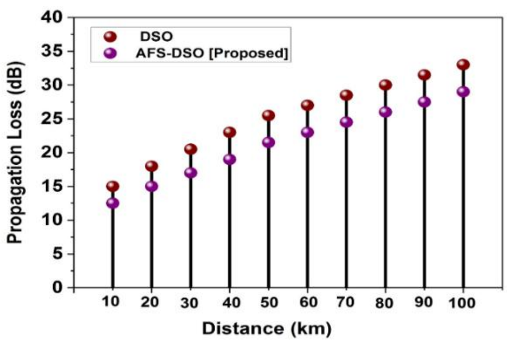

Fig. 1 – Graphical outcome of Propagation Loss of DSO and AFS-DSO

Table 2 shows the decrease in the objective function value for DSO and the proposed AFS-DSO methods. In ten iterations, AFS-DSO yields a better objective function solution compared to DSO with a reduction from iteration 1 at 0.75 to iteration 10 at 0.38. On the contrary, the case of DSO is displayed with a relatively less decline, it reaches a final value of 0.5.

Table 2 – Objective function minimization across iterations

Iterations	Objective Function Minimization	
	DSO[18]	AFS-DSO [Proposed]
1	0.75	0.65
2	0.7	0.6
3	0.65	0.55
4	0.62	0.52
5	0.6	0.5
6	0.58	0.48
7	0.58	0.45
8	0.53	0.43
9	0.52	0.4
10	0.5	0.38

The objective function minimization for DSO and the suggested AFS-DSO are graphically represented in Figure 2. The graph indicates that objective function values are reduced across iterations and objectives both in DSO and AFS-DSO models, with the AFS-DSO model obtaining relatively lower values in comparison with the DSO model. This fixed comparison reveals that AFS-DSO is certainly more improved by the optimization of the objective function, which states a fine-tuned advancement of the method in the domain of optimization.

Table 3 gives the values of convergence rates for DSO and the AFS-DSO for ten iterations. The results shown for both methods are consistent, as well as the rates of convergence of both are gradually decreasing toward

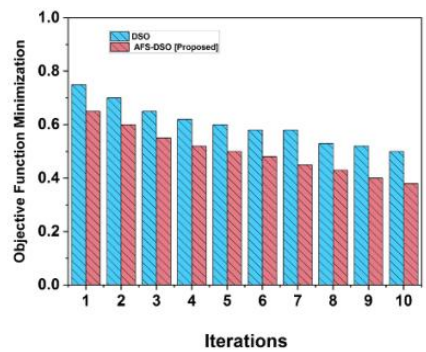

Fig. 2 – Graphical Presentation of Objective Function Minimization of DSO and AFS-DSO

a more stable optimum solution. In general, when observing the graph with the convergence rates of both methods, .however, the rates of AFS-DSO are slightly higher in the first iterations. This observation is useful in showing that AFS-DSO convergence in general can be faster than the traditional DSO, hence the potential of AFS-DSO in optimization tasks.

Table 3 – Numerical values of convergence rates

Iterations	Convergence Rates	
	DSO [18]	AFS-DSO [Proposed]
1	0.8	0.75
2	0.78	0.74
3	0.75	0.72
4	0.73	0.7
5	0.71	0.68
6	0.7	0.67
7	0.68	0.65
8	0.67	0.64
9	0.66	0.62
10	0.65	0.6

6. CONCLUSION

It exposes the benefits of using the proposed AFS-DSO technique in the estimation of surface ducts in electromagnetic propagation environments. When compared to the conventional DSO method, the enhancement by AFS-DSO is effective in reducing the propagation loss, improving the rate at which they converge, and modelling clutter power to facilitate accurate radar and radio signal transmissions. Thus, it identifies and observes the environmental factors affecting duct formation and improves the MMPE modelling assumption to create reliability in the communication and surveillance applications. Furthermore, the aspect of computational complexity may be a constraint in real-time operation in dynamic environments. The machine learning algorithms were used to advance optimization methodologies. Moreover, a demonstration of extending the models to various types of materials and environmental settings could provide more support.

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Розробка нового методу оптимізації для оцінки поверхневих каналів на основі тонкоплівкової технології

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Поверхневі канали – це добре спостережуване явище в атмосферному повітряному просторі, коли тонкий шар повітряного простору утворюється ближче до поверхні, що збільшує діапазон поширення електромагнітних сигналів. Цей ефект каналів може покращити передачу радіолокаційних та радіосигналів, що впливає на засоби зв'язку та спостереження. Фактори навколишнього середовища на місці можуть впливати на формування каналу та залежність від певного набору припущень моделювання, зроблених за допомогою підходу параболічного рівняння Монтерея-Маямі системи каналів. Для більш ефективної оцінки поверхневих каналів у цьому дослідженні використовується метод динамічної оптимізації чайок, керованої штучним роєм риб. Використовуючи кілька ітерацій, дослідження досліджує втрати на поширення, цільову функцію, швидкість збіжності та моделювання потужності перешкод як атрибутів поширення електромагнітних хвиль. Ефективність запропонованого методу динамічної оптимізації чайок вища, ніж традиційний метод. Результати показують ефективність покращення порівняно з базовим рівнем за допомогою гібридних алгоритмів оптимізації, які можуть покращити оцінки поверхневих каналів для радіолокаційних та тонкоплівкових застосувань.

Ключові слова: Поверхневий канал, Поширення електромагнітних хвиль, Параболічне рівняння Монтерея-Маямі, Динамічна оптимізація чайок, керована штучним роєм риб, Радіолокаційні системи.