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Genetic algorithm for accurate modeling of distributed Bragg reflector laser power and wavelength

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Abstract. We propose a modeling methodology tailored to predicting the wavelength and power output from a distributed Bragg reflector laser for use in quantum measurements. The relationship between power, wavelength, current, and temperature is acquired with a genetic algorithm (GA). The function set and termination set for GA are determined from the physical mechanisms of laser current, temperature, and output performance. To verify the validity of the method, measured data are divided into a training group and a test group. The test results show that our models can accurately predict the value of power and wavelength at the given current and temperature, with the RMSE of 13.4 μ W and 6.0×10^{-5} nm, respectively. This method can help enhance the output performance of a laser. © The Authors. Published by SPIE under a Creative Commons Attribution 4.0 Unported License. Distribution or reproduction of this work in whole or in part requires full attribution of the original publication, including its DOI. [DOI: [10.1117/1.OE.58.2.026108](https://doi.org/10.1117/1.OE.58.2.026108)]

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1 Introduction

Currently, the small volume and narrow line width of a distributed Bragg reflector (DBR) laser have been exploited for pumping and probing in atomic gyros and magnetometers.¹⁻³ It is reported that the accuracy and sensitivity of quantum measurements are directly limited by photon thermal noise and light shift of pump and probe beams,⁴⁻⁷ thus they should be suppressed to the utmost. Frequency and output power stabilization are common requirements, which can reduce photon thermal noise and light shift.

Since laser power and frequency stability are affected by environmental and electronic noise, it is necessary to find a power and frequency stabilization method.⁸ Modulators, such as an acousto-optic modulator and electro-optic amplitude modulator,⁹ are commonly used as actuators to stabilize the output power. The aim of frequency stabilization is to lock the laser to a reference frequency. Some notable frequency stabilization methods include Zeeman frequency stabilization method¹⁰ and polarization spectroscopy method.¹¹ However, both the power and stabilization methods require various optical devices and specific circuit systems, which cannot be used in highly integrated systems. For example, such methods are not applicable in a nuclear magnetic resonance gyroscope,¹² which is known for its miniaturization.

The power and frequency output performance of a DBR laser is grating period dependent, which is tuned by the temperature and current.¹³ When the current exceeds the threshold, the power increases linearly as the current rises. The power decreases with the heat accumulation. Moreover, if the temperature increases by 1°C, the wavelength will increase by about 0.3 nm in the near-infrared band. The power also varies with current fluctuations,

where the rate is ~ 0.01 nm/mA.¹⁴ A precise quantitative model to express the relationship is required. Once the effect of injection current and junction temperature on the laser wavelength and power become clear, the laser frequency and power can be stabilized with no need for auxiliary control equipment and optical devices.

The influence of current and temperature on the laser frequency and power can be analyzed with the semiconductor physics theories and quantum physics principles. There is a widely accepted output power model, but many parameters should be predetermined before it can be practically applied.¹⁴ Furthermore, temperature drift caused by the thermal effect of current has not been taken into careful consideration. There is no universally accurate quantitative model or modeling method for frequency stabilization until today. Many people have also attempted to model this relationship with artificial intelligence algorithms. However, this approach requires users be knowledgeable in laser structures, light emitting mechanisms, etc. Therefore, the problem of feasible, convenient, and accurate modeling needs to be solved.

Common methods for modeling in unknown areas include particle swarm optimization, ant colony optimization algorithm, and genetic algorithm (GA).¹⁵⁻¹⁷ For the model of lasers, the accuracy and stability of the algorithm are most critical. GA can find the global optimal solution, instead of a local one, and it is strongly robust. Thus GA is the best choice. GA is an adaptive modeling method, which was developed in the last decade and has found extensive applications in nonlinear modeling for the following three advantages.¹⁷ First, GA can establish a model based on experimental data without any prior knowledge on the form of the model.¹⁸ Second, no matter what form of the model takes, extremely accurate mathematical functions containing the inputs and outputs can be obtained with GA.¹⁸ Third, a good model can be acquired with a small amount

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of data. Until now, GA has rarely been used in laser research. At the same time, given that the laser is a precision instrument, and it plays an important role in the atomic physics experiments and researches, the accuracy is the primary goal to be considered in this modeling.

In this paper, we use a GA-based method to build a model describing the relationship between the laser current, temperature, output power, and wavelength. The previous theory on the relationship of laser current, temperature, and output performance is studied to determine the function set and termination set. Multiple sets of data including current, temperature, power output, and wavelength are used to establish an analytical model. The results show that the model can accurately describe the effect of laser current and temperature on the output power and frequency, and the obtained model can subsequently be used for frequency and power stabilization later.

2 GA Theory and Modeling Analysis

2.1 GA Theory

The GA technique is inspired by Darwinian evolution and follows the law of survival of the fittest.¹⁹ This algorithm is popular in many fields for its self-organization, self-learning, and self-adaptation properties. Using a binary tree data structure, this algorithm selects the optimal individual in the child generations through natural selection and genetic mechanisms, including selection, crossover, and mutation.²⁰ The optimal individual selection criterion in the algorithm is defined using a fitness function. Initial individuals are generated randomly. Other individuals with high fitness are saved by the program automatically and enters the next generation through the genetic mechanism.

In the selection process, models for laser power and wavelength established by GA are chosen by evaluating the fitness function at each iteration. During selection, the program picks from the current existing models rather than generating a new combination of operators and constants. The structure of the model, like the various chromosomes in natural selection, is constantly changing via the crossover and mutation operations. Crossover and mutation change the model's binary tree composition and diversify the structure, thus supporting selection of the fittest model.

It should be noted that the elements in the function set are chosen after studying well-known theories,²¹ since these determine the model complicity. Generally, the elements in the function set include basic algebraic operators, Boolean algebraic operators, and some other user defined operators.²² The terminal set in GA contains input variables, numerical constants, logical constants, and so on. The tree-structured model is established by randomly selecting the elements from the function and terminal sets as the root node. The binary tree is extended by selection, crossover, and mutation process until termination criteria are reached. Usually, the termination condition is defined based on the number of generations.

2.2 Modeling $P - (I, T)$

To ensure the accuracy of the model, we analyze the classic model as a benchmark for selecting the function and termination sets. The output power of a semiconductor laser is studied by analyzing the carrier rate equation in

semiconductor physics. As a result, the mechanistic model for laser power output can be expressed as²³

$$P = \eta_d \frac{h\nu}{e} (I - I_{th}), \tag{1}$$

where P is the laser output power and η_d is the external differential quantum efficiency. h , ν , and e are the Planck constant, frequency, and electronic charge, respectively. I is the laser diode injection current, and I_{th} is the threshold current of the laser. Equation (1) indicates that the laser output power is linear with respect to the injection current, threshold current, and external differential quantum efficiency. Furthermore, as the temperature increases, the threshold current would increase, but the external differential quantum efficiency would decrease.²⁴ Obviously, the output power will increase with the increased current and decreased temperature.

The impact of junction temperature on the threshold current and external differential quantum efficiency are studied from its physical mechanism defined by the following equations:²⁴

$$I_{th} = I_0 \exp(T/T_0), \tag{2}$$

$$\eta_d = \eta_0 \exp(-T/T_1), \tag{3}$$

where I_0 is the threshold current at 0 K, and η_0 is the external differential quantum efficiency extrapolated to $T = 0$ K. T_0 and T_1 are the characteristic temperatures, which represent threshold current and external differential quantum efficiency sensitivity to temperature, respectively. Temperatures in Eqs. (2) and (3) are typically expressed in Kelvins. Equations (1)–(3) can be combined into the following form:

$$P = \eta_0 \frac{h\nu}{e} \left(-\frac{T}{T_1} \right) \left[I - I_0 \exp\left(\frac{T}{T_0} \right) \right]. \tag{4}$$

Referring to Eq. (4), we choose the function set and the terminal set of the $P - (I, T)$ model as $\{+, -, \times, \div, \exp, \ln\}$ and $\{x_1, x_2, x_3, A\}$, respectively. The terminal set is the set including all the independent variables, which can be written as $\{x_1, x_2, x_3\}$. $\{A\}$ is a random constant set containing the model coefficients. Since GA is applied to establish a model for the output power, current, and temperature, we let $\{x_1 = I, x_2 = T, x_3 = P\}$. The composition of elements determines that the model constructed by GA will be a double-input and single-output model, and the expression will involve one or more relations including simple arithmetic, exponential, and logic operations.

The fitness function plays an important role in GA modeling since it directly determines the efficiency of program execution and the accuracy of the constructed model. Usually, there are four kinds of fitness functions: raw fitness, standardized fitness, adjusted fitness, and normalized fitness.²⁰ Given the complexity of the laser power model and our demands, a raw fitness function is adopted due to its simple implementation. In this paper, a fitness function aiming to evaluate the fitness level of the model is designed based on the minimum variance principle, like most regression procedures. We take a segmented assessment methodology in order to more precisely describe the trend of power with varying current and temperature. That is to say, all the

test data in GA modeling are divided equally into several groups, and the minimum variance principle is applied to each part. The adaptive evaluation function used in GA modeling can be expressed as²²

$$F_{GP} = \sum_{j=1}^n \left\{ 1 - k \frac{\sum_{i=1}^m (D[i] - GP[i])^2}{\sum_{i=1}^m (D[i] - \text{avg}[j])^2} \right\}. \quad (5)$$

All measurement data are divided into n groups, with m data in each part. $D[i]$ is the i 'th laser output power measurement in each group, $\text{avg}[j]$ is the j 'th average of the measurements of the j 'th part, and $GP[i]$ is the i 'th solution of the GA model. For a specific set of measurements, $\sum_{i=1}^m (D[i] - \text{avg}[j])^2$ is a constant. Thus $\sum_{i=1}^m (D[i] - GP[i])^2$, which is related to the GA model, characterizes the accuracy of the fitting results.

2.3 Modeling $\lambda - (I, T)$

The refractive index of the semiconductor material and the laser wavelength corresponding to the band gap will change as temperature, carrier concentration, and electric-field intensity fluctuate. The DBR laser is a multielectrode structure with an internal grating reflector. Laser tuning is primarily achieved by changing the grating period and the effective refractive index, which is accurately controlled by current

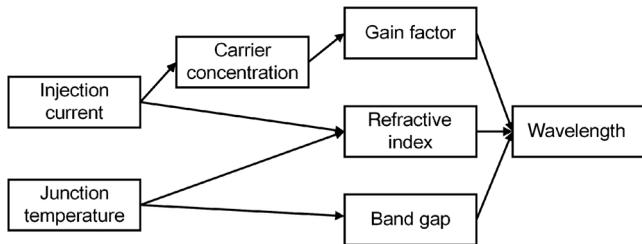


Fig. 1 Current and temperature are tuned by affecting the gain factor, carrier concentration, and band gap.

and temperature. To be more specific, once the injected current fluctuates, the carrier concentration will shift, which will lead to changes in the active area refractive index and material gain factor. A simultaneous temperature rise can change the refractive index and band gap of the material. The tuning mechanism is demonstrated in Fig. 1.²⁵

Although the output frequency from DBR laser has been discussed in many monographs, there is a lack of quantitative models for lasers with different output characteristics or in various operating conditions. Referring to the qualitative analysis above, we choose the function set and terminal set as $\{+, -, \times, \div, \exp, \ln\}$ and $\{x_4, x_5, x_6, B\}$, respectively, where $x_4 = I$, $x_5 = T$, $x_6 = \lambda$, and λ is the wavelength measured with a wavelength meter. As for modeling $\lambda - (I, T)$, the fitness function is shown as Eq. (5) as well, where measurements are wavelength in place of power.

3 Experiments and Result Analysis

3.1 Experimental Setup

A DBR laser is an instrument that converts electrical energy to optical energy. Generally, drive current is injected to the diode after the temperature of the heat sink settles, and the laser output can be affirmatory. Changes in the injection current and junction temperature can directly alter the output power and wavelength. The experimental setup is shown in Fig. 2. There are mainly data acquisition and GA modeling steps in our experiment. For data acquisition, a current controller and a temperature controller were used to drive the DBR laser diode. The laser is divided into two beams by a glass plate, and both beams are used for frequency and power measurements. The laser diode we used as the light source was PH852DBR (Photodigm) with 40- to 50-mA threshold current. A high-performance current controller (Thorlabs LDC205C) with a large range of 0 to ± 500 mA was used for driving the laser diode, and its ripple was no more than $2 \mu\text{A}$ at the full driving range. The temperature controller (Thorlabs TED200C) was used to measure the temperature in real time, and its output voltage, through

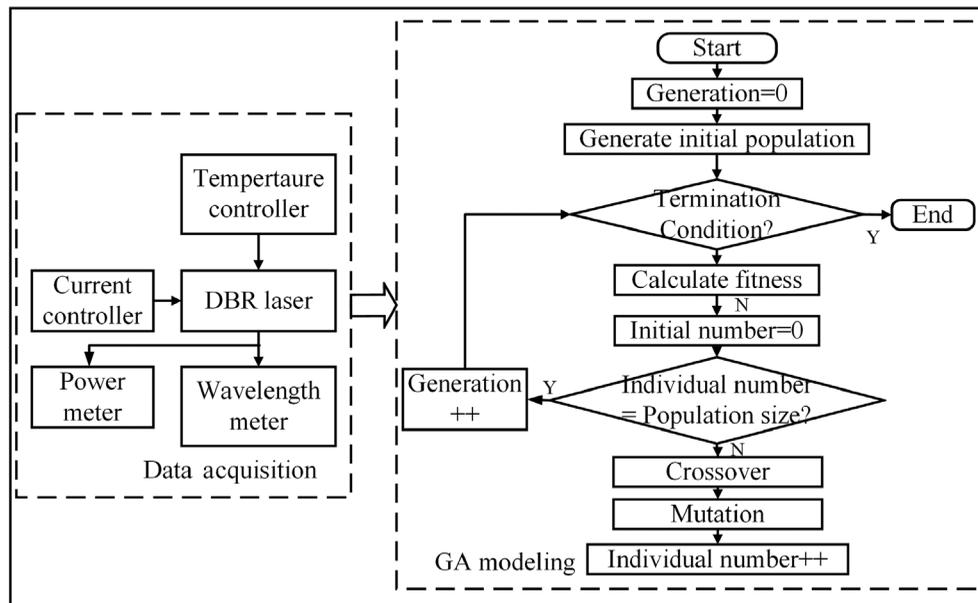


Fig. 2 Experimental setup.

Table 1 GA parameters.

Parameter	Value
Population size	200
Number of generations	200
Crossover probability	0.85
Mutation probability	0.10
Reproduction probability	0.05
Maximum tree depth	8

internal calculation, was used to drive a thermoelectric cooler. The temperature control range and stability are -25°C to 105°C and less than 2 mK, respectively. The power meter we used is PM100D (Thorlabs), the accuracy of which is only $\pm 3\%$. The wavelength of laser was measured with a wavelength meter (High Finesse WS7-60) with range from 192 to 2250 nm, with 60-MHz resolution.

During data acquisition, we measured the power and wavelength values by changing the current from 40 to 80 mA (0.5-mA increments), while temperature remains constant. The measurement process was then repeated by adjusting the temperature at constant current. Both processes were repeated three times, and the measured data were filtered by the 3σ principle. The 284 data points we collected were used to analyze the effect of injection current and junction temperature on the DBR laser output power and wavelength with GA. Among the experimental data, we select the first 200 data points (70.42%) as a training set and the remaining 84 points (29.58%), which were measured at 21.5°C , as the test data.

The GA modeling flow is mentioned in Sec. 2, as shown in Fig. 2. In order to obtain accurate models with the GA program, the GA parameters should be carefully selected to obtain the proper complexity and correlation coefficient of the fitting results, which indicate the quality of the established models. The GA parameters we used are shown in Table 1. Tournament selection is chosen for GA, since it has several advantages over other alternative selection methods: it is efficient to code, runs in parallel, and is easy to adjust.²⁶

3.2 Establishing the Model for $P - (I, T)$

The program repeats the calculations for the fitness function. Low-fitness individuals are eliminated until the optimal GA model is obtained. After simplifying the GA model and keeping the same valid figures as the original data, the GA model can be described as

$$\begin{aligned}
 P = & -8.656 \times 10^{-5}I^2 + 4.167 \times 10^{-3}IT - 1.757 \times 10^{-2}T^2 \\
 & -7.260 \times 10^{-2}I + 0.7980T + \frac{0.1040T - 6.506}{I} \\
 & + \frac{2.080I + 17.83}{T} - 13.46, \quad (6)
 \end{aligned}$$

where P is measured in mW, T is the junction temperature in $^{\circ}\text{C}$, and I is the injection current in mA. The correlation

coefficient (R^2) of this model exceeds 0.99999, whereas R^2 of the classic model is 0.9997. Although the DBR laser power seems to vary linearly with current and temperature fluctuations, the classical linear model cannot meet the standard for laser power prediction accuracy with large current and temperature fluctuations.

If we notice that the testing data are not used during the modeling process, they are irrelevant to the models we obtained. Therefore, we can use them to evaluate the performance of the models. The GA model is much better since the root-mean-square error (RMSE) of the GA model is 0.0134 mW, nearly one third of that for the classic model (0.0415 mW). By comparing the GA model for the laser output power with the classic model [described as Eq. (4)], we find that the two models mostly overlap from 47 to 75 mA. We also find that the classic model overestimates the power output at low- or high-injection current, particularly when the current slightly exceeds the threshold (~ 40 mA) or goes beyond 75 mA, as shown in Fig. 3. For the low-power probe light, below 5 mW usually, using GA method can reduce deviation by 0.1 mW or so. As a result, the uncertainty of optical rotation angle will decrease by over 5 deg, which will improve the accuracy of the atomic gyros and magnetometers, whose value is 8.11 deg per s.

The influence of current and temperature on the laser output power can be predicted easily with the GA model for injection currents ranging from 45 to 200 mA and for temperatures ranging from 21.5°C to 26°C , given the common controller parameters of the pump and probe laser. As the model describes, the output power of the DBR grows higher as the current increases or temperature decreases. Obviously, the output power exhibits a curvilinear rise as the current increases and as temperature stays constant over the range shown in Fig. 4, while the nonlinear relationship is not significant for power and temperature.

The forms and parameters of GA model depend on the characteristics of the laser. According to the classic model, the power of laser varies linearly with current at a constant temperature, whereas the linearity of the measurements is 0.9996 on average, experimental results shown. This will lead to an uncertainty of prediction for power, which is nearly 0.05 mW. The bias of classic model is more remarkable at the low power (less than 5 mW) and the high power (about or above 20 mW), and the error exceeds 0.1 mW. For atomic gyros and magnetometers, the probe beam is usually 3 mW or so, and the pump beam is usually beyond 20 mW. GA model provides a more accurate prediction, which will help to improve the performance of quantum sensors.

3.3 Establishing the Model for $\lambda - (I, T)$

The GA model we obtained can be expressed as

$$\begin{aligned}
 \lambda = & 9.9776 \times 10^{-8}I^2T + 2.3317 \times 10^{-6}I^2 + 1.1805 \times 10^{-3}I \\
 & -4.4710 \times 10^{-6}IT - 5.9186 \times 10^{-2}T + 851.0206, \quad (7)
 \end{aligned}$$

where λ is measured in nm, T is the junction temperature in $^{\circ}\text{C}$, and I is the injection current in mA. The R^2 value of this model is nearly 0.99999. Similarly, we also make use of the remaining set of data to test whether the predicted results are

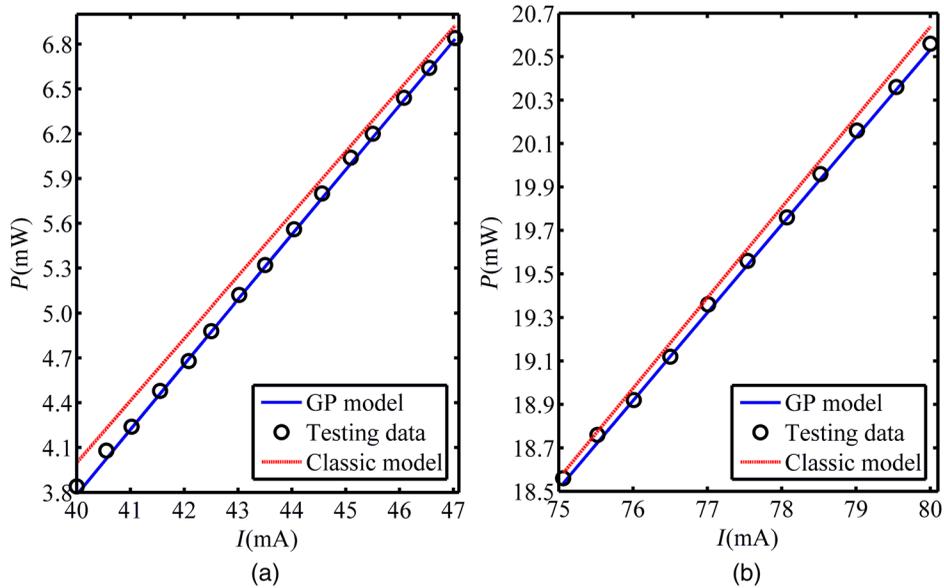


Fig. 3 (a) Comparison between classic model and GA model for current ranging from 40 to 47 mA and (b) comparison between the classic model and GA model for current ranging from 75 to 80 mA.

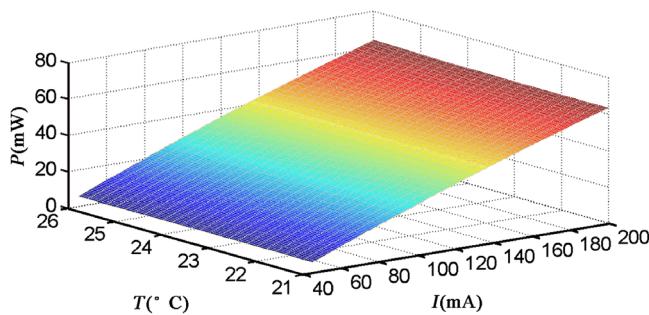


Fig. 4 Output power prediction with the $P - (I, T)$ model with current and temperature ranging from 45 to 200 mA and 21.5°C to 26°C, respectively.

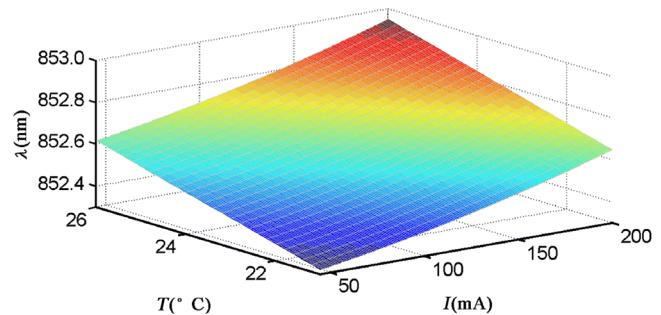


Fig. 6 Wavelength prediction with the $\lambda - (I, T)$ model with current and temperature ranging from 45 to 200 mA and 21.5°C to 26°C, respectively.

accurate enough, and the results are shown in Fig. 5. The RMSE of the fitting results is 6.0×10^{-5} nm.

Based on this model, we can predict wavelength fluctuations over a wide range of current and temperature changes, which is conducive to laser frequency stabilization and fast tuning. We use this model to predict the output wavelength under normal operating conditions as the control input changes, as shown in Fig. 6. Figure 6 describes a smooth

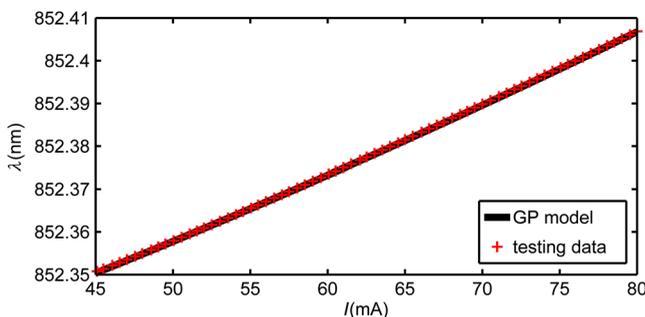


Fig. 5 Test results of the GA model.

surface with the wavelength changing linearly as temperature fluctuates and quadratically as current fluctuates.

4 Conclusion

In this paper, we proposed a GA-based modeling method for determining the output power wavelength, injection current, and junction temperature in a DBR laser. The predicted output power results are more accurate than those from the classic model, especially when the current is larger than 75 mA or smaller than 47 mA (i.e., higher than threshold). Moreover, RMSE of our model ($14.3 \mu\text{W}$) is only one third that from the classic model. As for wavelength, we obtained a quantitative model to detail how the injection current and temperature influence the wavelength, with an RMSE of 6.0×10^{-5} nm, which is more accurate than most wavelength meters on the market. It can solve the problem that there is rarely universal quantitative relationship for now. Models for different laser diodes can be obtained by measuring the power and frequency corresponding to some values of current and temperature, followed by adjusting the parameters in the program appropriately. This method can create precise model of laser output performance with no prior knowledge, which promises to be one of the most

widely used method for stabilizing the output power and frequency.

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References

1. Y. Zhai et al., "Talbot-enhanced, maximum-visibility imaging of condensate interference," *Optica* **5**(1), 80–85 (2018).
2. H. Jeff, "A short history of laser development," *Appl. Opt.* **49**(25), F99–F122 (2010).
3. B. Benoit et al., "Quantum manipulation of two-electron spin states in isolated double quantum dots," *Phys. Rev. Lett.* **115**(9), 096801 (2015).
4. I. Yosuke et al., "Effect of spatial homogeneity of spin polarization on magnetic field response of an optically pumped atomic magnetometer using a hybrid cell of K and Rb atoms," *IEEE Trans. Magn.* **48**(11), 3715–3718 (2012).
5. W. Du et al., "New phenomena in laser-assisted scattering of an electron by a muon," *Front. Phys.* **13**(4), 133401 (2018).
6. R. Rajan et al., "Photon condensation: a new paradigm for Bose–Einstein condensation," *Front. Phys.* **11**(5), 110502 (2016).
7. T. L. Nicholson et al., "Comparison of two independent Sr optical clocks with 1×10^{-17} stability at 10^3 s," *Phys. Rev. Lett.* **109**(23), 230801 (2012).
8. D. K. Srivastava et al., "Effect of laser pulse energy on the laser ignition of compressed natural gas fueled engine," *Opt. Eng.* **53**(5), 056120 (2014).
9. P. Kwee et al., "Shot-noise-limited laser power stabilization with a high-power photodiode array," *Opt. Lett.* **34**(19), 2912–2914 (2009).
10. G. Budzyń et al., "Method of improving the frequency repeatability of the intensity stabilized He-Ne laser," *Laser Phys.* **25**(6), 065002 (2015).
11. Y. Shindo, "Application of polarized modulation technique in polymer science," *Opt. Eng.* **34**(12), 3369–3385 (1995).
12. W. Quan et al., "Far off-resonance laser frequency stabilization using multipass cells in Faraday rotation spectroscopy," *Appl. Opt.* **55**(10), 2503–2507 (2016).
13. H. Liu et al., "Tuning characteristics of monolithic passively mode-locked distributed Bragg reflector semiconductor lasers," *IEEE J. Quantum Electron.* **32**(11), 1965–1975 (1996).
14. W. Demtroeder, *Laser Spectroscopy: Basic Concepts and Instrumentation*, Springer, Berlin, Heidelberg (1981).
15. P. Ghamisi et al., "Feature selection based on hybridization of genetic algorithm and particle swarm optimization," *IEEE Geosci. Remote Sens. Lett.* **12**(2), 309–313 (2015).
16. M. Mahi et al., "A new hybrid method based on particle swarm optimization, ant colony optimization and 3-opt algorithms for traveling salesman problem," *Appl. Soft Comput.* **30**, 484–490 (2015).
17. J. R. Koza et al., *Genetic Programming IV: Routine Human-Competitive Machine Intelligence*, Springer Science and Business Media, Berlin, Heidelberg (2006).
18. W. Quan et al., "Modeling and optimizing of the random atomic spin gyroscope drift based on the atomic spin gyroscope," *Rev. Sci. Instrum.* **85**(11), 113104 (2014).

19. M. I. Kim et al., "Modeling of drilling forces based on twist drill point angles using multigene genetic algorithm," *Math. Prob. Eng.* **2016** (2016).
20. S. Karakatić et al., "A survey of genetic algorithms for solving multi depot vehicle routing problem," *Appl. Soft Comput.* **27**, 519–532 (2015).
21. Y. S. Lee et al., "Forecasting time series using a methodology based on autoregressive integrated moving average and genetic programming," *Knowl. Based Syst.* **24**(1), 66–72 (2011).
22. W. Quan et al., "Locking distributed feedback laser diode frequency to gas absorption lines based on genetic programming," *Opt. Eng.* **56**(1), 016106 (2017).
23. A. Zybin et al., "Diode laser atomic absorption spectrometry," *Spectrochim. Acta Part B* **60**(1), 1–11 (2005).
24. J. I. Pankove, "Temperature dependence of emission efficiency and lasing threshold in laser diodes," *IEEE J. Quantum Electron.* **4**(4), 119–122 (1968).
25. M. Happach et al., "Temperature-tolerant wavelength-setting and-stabilization in a polymer-based tunable DBR laser," *J. Lightwave Technol.* **35**(10), 1797–1802 (2017).
26. B. L. Miller et al., "Genetic algorithms, tournament selection, and the effects of noise," *Complex Syst.* **9**(3), 193–212 (1995).

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