UNIVERSITI PUTRA MALAYSIA

AN IMPROVED PARAMETRICAL OPTIMIZATION OF SUPERCONDUCTING ENERGY STORAGE RINGS VIA QUANTUM PARTICLE SWARM OPTIMIZATION APPROACH

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BY

NURUL SYAZANA BINTI NORDIN

Thesis Submitted to the Department of Physics, Universiti Putra Malaysia, in partial Fulfilment of the Requirements for the Degree of Bachelor of Science in Instrumentation Science with Honours

February 2022

DEDICATION

This thesis is dedicated to:

My parents, En. Nordin bin Yatim and Pn. Kalsom binti Pardi;

For their unwavering belief in me, their love, and their support.

My project supervisor, Dr. Edgar Scavino;

For allowing me to gain knowledge and experience

My lecturers;

For continually working and assisting me greatly along this journey

My beloved friends;

For all the happiness and pleasant memories, always connected in spirit

And to all who assisted in the preparation of this thesis.

ABSTRACT

An Improved Parametrical Optimization of Superconducting Energy Storage Rings Via Quantum Particle Swarm Optimization Approach

By

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February 2022

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A new improved version of an Intelligent Particle Swarm Optimization (IPSO) algorithm, is applied for the design of a Superconducting Magnetic Energy Storage (SMES) device. Quantum inspired particle swarm optimization (QPSO) is widely used global convergence algorithm for complex design problems. This algorithm is a population based optimal method and very simple in both theory and numerical implementation. Nowadays, it has been recognized as a paradigm for numerical optimizations. In 1996, a superconducting magnetic energy storage arrangement was selected to become a benchmark problem for testing different optimization algorithms, both deterministic and stochastic ones. Since the forward problem can be solved semianalytically by Biot Savart's law, this benchmark became quite popular. In this paper, a new version of the design TEAM benchmark 22 will be made and some results will be presented..

ABSTRAK

Pengoptimuman Parametrik bagi Gelang Penyimpanan Tenaga Superkonduktor Melalui Pendekatan Pengoptimuman Swarm Zarah Kuantum

Oleh

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Satu versi baharu algoritma Pengoptimuman Swarm Zarah Pintar (IPSO) telah digunakan pada reka bentuk Penyimpan Tenaga Superkonduktor (SMES). Pengoptimuman Swarm Zarah Kuantum (QPSO) digunakan secara meluas untuk algoritma penumpuan global dalam masalah reka bentuk yang kompleks. Algoritma ini adalah kaedah optimum berasaskan populasi dan sangat mudah diaplikasi pada keduadua pelaksanaan teori dan berangka. Pada masa kini, ia telah dikenali sebagai paradigma kepada pengoptimuman berangka. Pada tahun 1996, susunan penyimpanan tenaga magnet superkonduktor telah dipilih untuk menjadi masalah penanda aras untuk menguji algoritma pengoptimuman yang berbeza. Memandangkan masalah hadapan boleh diselesaikan secara semianalitik oleh peraturan *Biot Savart*, penanda aras ini menjadi agak popular. Dalam kertas kerja ini, versi baharu reka bentuk penanda aras TEAM 22 akan dibuat dan beberapa keputusan akan dibentangkan.

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All praise to Allah the Almighty who have given me the strength, guidance and blessing more than I deserved.

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May Allah S.W.T shower the above-cited personalities with success and honour in their life.

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LIST OF ABBREVIATIONS

cQPSO	Cellular Quantum-Behaved Particle Swarm Optimization
DC	Direct Current
GQPSO	Gaussian Quantum Particle Swarm Optimization
PSO	Particle Swarm Optimization
QPSO	Quantum-Behaved Particle Swarm Optimization
SMES	Superconducting Magnetic Energy Storage

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Quantum-behaved particle swarm optimization (QPSO) is a global optimization method that combines particle swarm optimization (PSO) and quantum mechanics. It outperforms in terms of search capability, convergence speed, solution accuracy, and problem-solving resilience. SMES systems consisting of single superconducting solenoidal coil offer in magnetic fields in a fairly simple and economical way, and can be rather easily scaled up in size. The benchmark problem to test electromagnetic optimization of SMES was found in 1996. (Alotto et al. 1996) Over time and demand, many researches have been study and used this benchmark and the parametric optimization has been improved. The optimization results of the new parameter instead of the old rectangular coil was obtained using Gaussian Quantum Particle Swarm Optimization.

1.2 Problem Statement

The SMES problem we address is comprised of two concentric coils conveying current in opposing directions and operating under superconducting conditions, allowing us to store a substantial amount of energy in their magnetic fields while maintaining the stray field below specified limitations. An ideal system design should therefore combine the desired amount of energy to be stored with the least amount of stray field while not breaching the quench requirement. The specifications for minimum and maximum values must be followed. In fact, the problem parameters, since the current densities for any fixed geometric design can be estimated via quadratic optimization so that the stored energy in the device is exactly the needed value.

1.3 Objective

The primary goal of this research is to contribute to a better understanding of the algorithmic structure and search behaviour of QPSO in relation to major parameter adaptation of storage ring. To sum up, main objective is:

1. To calculate magnetic field in toroidal configuration of coil.
2. To optimize resistance, radius of torus and current while keeping given energy and quench condition.
3. To apply to 1 and 2 concentric coils.

1.4 Significant of Study

Artificial intelligence has been used in research studies to enhance process optimization in computer systems while also decreasing complexity. Swarm Intelligence is an Artificial Intelligence area that analyses the collective behaviour of social swarms in nature, such as ant colonies, honey bees, and bird flocks. The methods discovered through swarm observation have been found to provide process optimization advantages. In this work, a hybrid version of these algorithms is employed as an alternative to the existing and inefficient signature techniques of task scheduling in operating systems.

The research study uses Quantum Particle Swarm Optimization to enhance and optimise Superconducting Magnetic Energy Storage (SMES). The classifier's function and parameters were optimised. Experiments are carried out in the MATLAB software environment.

1.5 Overview of Thesis

Chapter 1 gives an introduction of a significant viewpoint or component that plays prominent roles in this research, the background studies of benchmark problem, electromagnetic energy, QPSO. It presented a general explanation of structural investigations in Chapter 2. It additionally clarified about the problem statement, objectives and limitation of this research. Next, Chapter 2 gives a review of related literature reports that are significant with this project and some background knowledge or data to acquire research information. Then, in Chapter 3 devoted on the methodology to conduct this research, like the superconducter condition, deriving the equation and how the result satisfy the quench are obtained. Next, in Chapter 4, the result of magnetic field and optimum parameter is discussed. Finally, Chapter 5 concludes all these research studies and the recommendations for this project's future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of previous study and relevant literature related to the element and process that has been used in this study. The optimization strategy is also would be further discuss as it is the main objective in this study.

2.2 Superconductivity

Superconductivity offers, in principle, the best method of storing electric power and one of the few methods of directly storing electromagnetic energy. The storage system is made comprised of a superconducting material coil that is maintained extremely cold. Off-peak power is converted to direct current (DC) and sent into a storage ring via a converter system, where it remains until it is needed. The energy is actually stored as a magnetic field that keeps the current flowing; in fact, the two are mutually supportive, and with no resistive energy loss, the current will continue to cycle eternally. If the system is kept below a specified temperature, the stored energy in the ring will not be lost.

Superconductivity is a unique characteristic of some materials that occurs at low temperatures when resistance is zero. As a result, superconducting materials may carry current with no power dissipation due to the Joule effect. For large magnet systems, such as those used in storage rings, this has at least two advantages: (1) a considerable reduction in electrical power usage, and (2) the ability to rely on considerably greater overall current densities in the magnet coils.

The SMES device relies on a family of materials known as superconductors. Below a specific temperature known as the transition temperature, which is unique to each material, superconductors experience a fundamental shift in their physical characteristics.

Before becoming superconducting, the best metallic superconducting materials available today must be cooled to temperatures close to absolute zero. The most widely used and cheapest superconducting material is a niobium-titanium alloy that has a critical temperature of 10°K or 263^{0}C. To keep a coil composed of the alloy below this temperature, liquid helium is typically employed as a coolant. Niobium-titanium alloys can withstand quite high magnetic fields. Other, more expensive materials are also available if a high magnetic field is required.

Scientists have just found a new class of ceramic materials that turn superconducting at relatively high temperatures, temperatures that can be reached by cooling with liquid nitrogen. (Liquid nitrogen boils at 98^{0}K - 175^{0}C.) Most of these materials have proved to be rather brittle ceramics that are difficult to work but techniques are being found to exploit them.

Fig. 2.1 illustrates an example modest commercial SMES system that could be utilised for grid stability applications. The compact SMES storage ring of this system is built into a container for simplicity of transportation and installation. The storage ring is linked to the electrical distribution system at the required location. Grid power is utilised to power the cooling system, which keeps the actual storage ring below its critical temperature. The grid is then used to charge the SMES ring. In this situation, the ring will be employed to maintain grid stability or power conditioning. Sensors will monitor the grid's status, and if there are changes in frequency, voltage, or phase, power can be pulled from the ring to fix the instability.

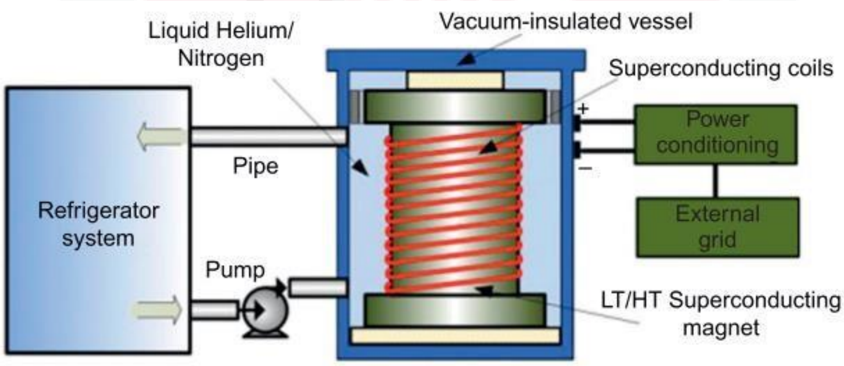


Figure 2.1: Schematic of distributed SMES system.

One of the fundamental problems about SMES is whether it is better to utilise hightemperature superconductors that require only liquid nitrogen to cool them or lowtemperature superconductors that require liquid helium or liquid hydrogen to cool them. While high-temperature materials appear to be less expensive, their physical and electrical qualities indicate that far more of this type of material is required to give a ring with the same storage capabilities as a ring utilising a low-temperature superconductor.

2.3 Quantum Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary computation method created by Dr. Eberhart and Dr. Kennedy in 1995 in response to the social behaviour of flocking birds and schooling fish. Individuals exchange information in order to find the best answer. However, under acceptable conditions, the algorithm does not converge to the global minimum point with probability one, hence a global convergence-guaranteed PSO technique has been created (Sun, Feng, and Xu 2004). The QPSO (Quantum-behaved Particle Swarm Optimization) method is based on quantum mechanics. It has been proven that QPSO outperforms PSO in numerous areas, including simple evolution equations, fewer control parameters, rapid convergence time, and ease of use.

The particles of the QPSO algorithm can appear in any search space and are based on the delta potential. At the same time in the quantum search space, the positions and velocities of the particles can't be calculated. The wave function $\Psi(X, t)$ used to calculate the state of the particle. In the certain position, the formula $|\Psi(X, t)|^2$ used to find the probability of the particles, then the probability distribution function can be measured. Each particle must have a location, which may be computed and updated using the following: Eq. (1)

$$\text{Xid} = \text{pjd} \pm 0.5\text{Aln}\left(\frac{1}{u}\right) \sim U(0,1) \tag{1}$$

Where P_{jd} and $U(0,1)$ are the local attractor, and random number respectively. The value of the random number $U(0,1)$ between 0 and 1. The P_{jd} can measured by the following Eq. (2).

$$p_{jd} = \beta P_{jd} + (1-\beta) P_{gd} \beta \sim U(0,1) \tag{2}$$

Where the best position of the j^{th} particle is defined as $P_j = (P_{j1}, P_{j2}, P_{j3}, \ldots, P_{jd})$, the global position of all particles is defined as $P_g = (P_{g1}, P_{g2}, P_{g3}, \ldots, P_{gd})$; and β is the random number. The value of β distributed between 0 and 1. The parameter A measured by Eq. (3).

$$A = 2\alpha . \mid mbest_{\,d} - X_{jd} \mid \tag{3}$$

Where the average optimal position of all the particles is $mbest$. The $mbest$ is measured by following Eq. (4).

$$mbest = \frac{1}{M}\sum_{j=1}^{M} pbest_j \tag{4}$$

The parameter α is the contraction-expansion coefficient. The parameter α can be calculated as the following Eq. (5)

$$\alpha = 0.5 + 0.5 \times \frac{(L_C - C_C)}{L_C} \tag{5}$$

Where L_c and C_c are the total number and the current number of iterations respectively.

In QPSO, particles search throughout the whole solution space in quantum space for the global optimum. cQPSO is a quantum-inspired PSO with a cellular structured swarm, in which particles are placed in a two-dimensional grid and can only communicate with their immediate neighbours (Fang et al. 2016). When compared to other swarm-based algorithms, the experimental and statistical analysis findings demonstrated that the cQPSO performed better with local best (Houssein et al. 2021).

A swarm of particles, each representing a solution, moves across parameter space in search of the best solutions; the movement of the particles is modified by their current speed, the best known locations, and the historical best position.

In Newtonian mechanics, the particle follows a predetermined path, but this is not the case in quantum mechanics. The word "trajectory" has no relevance in the quantum universe since the uncertainty principle prevents knowing a particle's location and velocity at the same time. As a result, if individual particles in a PSO system display quantum behaviour, the PSO algorithm would most likely act differently as well. Jun Sun et al. introduce the QPSO algorithm in a quantum time-space context. The equations are as follows

$$p_{id} = \varphi \times pbest_{id} + (1 - \varphi) \times gbest_d \tag{6}$$

$$\text{xid}(t + 1) = \text{pid} \pm \beta \mid \text{mbest d} - \text{xid}(t) \mid \times \ln\frac{1}{u} \tag{7}$$

where is a uniformly distributed random number (0,1). The population's mean best position is mbest. The Contraction-Expansion coefficient is a parameter that may be tweaked to modify the algorithm's convergence pace. It may be deduced from the findings of stochastic simulation (Jun Sun et al.) that the particles in QPSO will converge around 1.782. When the random number is greater than 0.5, the negative sign (-) is recommended, and when it is greater than 0.5, the plus sign (+) is proposed.

Particles in quantum systems display quantum activity by travelling through Hilbert space. The particle is drawn by a quantum potential well towards its local attractor in this technique, yielding the stochastic updating equation for the particle's location. It is generally recognised that the two most important decisions in balancing the QPSO's diversification and intensification capabilities are the suitable parameter selection and the algorithm's ability to govern the swarm diversity wisely. (Agrawal, Kaur, and Agarwal 2021). As a result, particles further from the swarm's centre will have a greater searching scope, whereas particles in the centre will only be able to search in a very limited little space.

The results reveal that the particle swarm method converges to comparable or superior solutions far quicker than the genetic algorithm, and it does so without the need for suitable solutions to be seeded in the starting population. (Huang and Safranek 2014)

2.4 Parametric Optimization

The purpose of this paper is to offer an overview of parametric optimization outcomes that might be considered classic results on the subject. We work with programmes of this form: For t in a parameter set $T \subset \mathbb{R}^p$ we wish to find local minimizers $x = x(t)$ of

$$P(t): \min_{x \in \mathbb{R}^n} f(x,t) s.t. x \in F(t) = \{x | g_j(x,t) \leq 0, j = 1, \dots, m\} \qquad (8)$$

Note that for any fixed parameter $\bar{t} \in T$, the program $P(\bar{t})$ represents a standard optimization problem. Suppose for fixed t^{-} we have given the feasible set $F(\bar{t})$, and a local minimizer $\bar{x}$ of $P(\bar{t})$ with corresponding value $v(\bar{t}) = f(\bar{x},\bar{t})$.

For all practical purposes, linear is always parametric. The inertia weight (w), learning factors (c_1 and c_2), and maximum velocity (V_{max}) of the particle swarm algorithm all have a significant impact on the method's overall performance. The larger the value of inertia weight, the better the algorithm's global search capabilities. Learning factors (c_1 and c_2), are primarily utilised to regulate particles approaching the individual and swarm optimum locations.

The asynchronous time varying learning factor approach is used. With each repetition, cognitive learning component (c_1) decreases while the social learning factor c_2 increases, ensuring that particles have a better global search ability in the beginning and a greater social learning capacity in the latter period (Zhang et al., 2020).

2.5 Optimization with Regards to Stray Field

When investigating coil arrangements it soon turned out that the number of independent parameters were countless. This required restrictions in order to be able handle the various parameters and to find some optimization strategies. An important parameter is certainly the amount of stored energy, which was set to be 180MJ.

The size of the planar coil configurations represented in Fig. 2.2 were designed with the goal of minimising the magnetic stray field in mind. The need for small dimensions comes from rising land prices, as a SMES system might be developed in densely populated regions.

Since the stored energy was determined, the currents in both coils were computed using the inductance coefficients, in accordance with the law.

$$W = \frac{1}{2} \cdot L_1 \cdot I_1^2 + \frac{1}{2} \cdot L_2 \cdot I_2^2 - M \cdot I_1 \cdot I_2 \quad (9)$$

In order to satisfy magnetic moment that are identical but in opposite direction,

$$m = IA \quad (10)$$

the current in the inner solenoid has to be much higher than in the outer solenoid, which implies that most of the energy of the whole system is stored in the inner coil. This was the reason why the aspect ratio of the inner coil was set to be $\beta = 0.2$, as it is recommended. As a matter of fact, as the coil radius increases, the aspect ratio of the outer coil drops in order to have a smaller currents flow in there. However, because the aspect ratio in the outer coil has been reduced, the current densities in both coils may be kept constant. This is a significant fact since it enhances the use of a superconductor. After all these simplifications three parameters remain, which are the outer coil radius R, the current densities in both coils J and η, the ratio of the outer coil radius to the radius of the inner coil.

The self as well as the mutual inductances have been calculated from Table 2.1. Fig 2.2 shows the coil arrangement with its annotations. Simplifying the equation for the stored energy by introducing certain abbreviations and relations, gives the result for the outer radius, which depends on the parameters J and η.

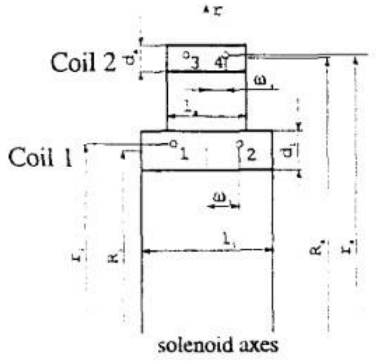


Figure 2.2: The coil arrangement

Table 2.1: Result of different optimization approaches

	Analytical approach	Evolution strategy ($q_{EV,1}$)	Evolution strategy ($q_{EV,2}$)	Conjugate gradient method	Coupled method (ES+CG)
$R_1(m)$	2.93	1.99	2.325	2.71	2.04
$R_2(m)$	3.66	2.93	3.201	3.56	2.98
$I_1(m)$	1.17	1.29	1.21	1.01	1.26
$I_2(m)$	0.937	0.92	0.988	0.735	0.92
$d_1(m)$	0.293	0.29	0.285	0.293	0.29

$d_2(m)$	0.234	0.188	0.186	0.234	0.188
J($\frac{A^2}{mm}$)	23.60	26.20	25.31	26	26.24
Distance in z direction (m)	23.2	18.9	19.60	20.3	116.8
Distance in r direction (m)	19	18	18	20.2	21
Total number of FE calculations	-	933	266	105	60(ES)+50(CG)
"feasible" FE calculations	-	300	199	105	50(ES)+50(CG)
Energy(kWh)	50	50	50	50	50

2.6 Effect of Quench

The particularly of the SMES problem is that, on the one hand, some configurations in the searching domain are not allowed, due to a restriction given by the quench condition, which, if it is violated, the superconducting state is lost.

Superconductors show critical behavior concerning their current densities and applied field densities. Superconductors are able to transport rather high current densities but if the applied field is too high, the superconductor will change into normal resistive state and release all its stored energy at once. In Fig. 2.3, the curve was considered to be a straight line, which is easier to deal with numerically. So, it is important to determine the position within the coils where the magnetic flux density has its peak value.

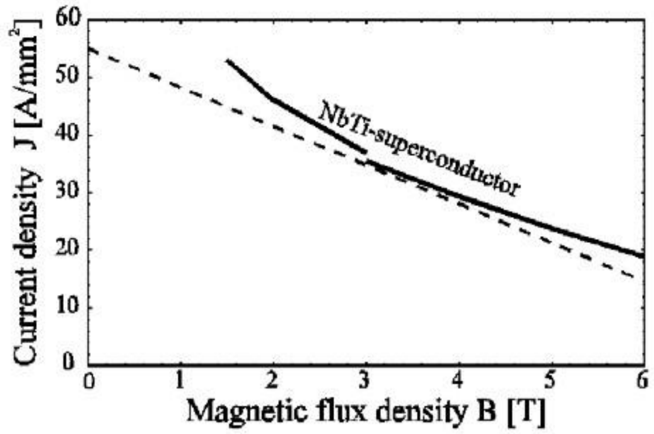


Figure 2.3: critical curve of an industrial superconductor

The most destructive impact of a quench is that it wastes power through the Joule effect after a volume of conductor has transitioned to the usual resistive state. The majority of this energy is used to heat the conductor locally. The conductor temperature can approach room temperature in a very short period (usually a few tenths of a second) and continues to rise if the magnet is not discharged.

All of the magnetic energy held in a quenching magnet must be converted into resistive power before it can be discharged. If the quench propagates slowly, a considerable portion of the stored energy may be wasted in a small volume of conductor. In the event of a string of magnets connected electrically in series, the energy of the entire string may be wasted in the quenching magnet. As a result, in order to avoid burnout, the usual resistive zone must expand fast across the quenching coil.

2.7 Proposed Formulation

In the tree parameters version, the current density is equal to 22.5A/mm^2, which gives

$$B_{max} \leq 4.92T \tag{11}$$

as the inequality constraint for the quench condition.

A solution that is much below the limit, on the other hand, is subtilizing the superconducting material since the current density may be higher. A solution that is too near to the critical limit, on the other hand, would be problematic, because even a little change in the current density may cause the device to lose superconductivity. Even if the linearization curve is already slightly lower than the real curve, the designer can still set a safe limit level.

$$|B_{max,i}| \leq \frac{54.0 - |J_i|}{64} - \xi_i, i = 1.2 \tag{22}$$

Where $B_{max,i}$ is the maximum magnetic flux density in at coil i, J_i is the current density in A/mm^2 for the coil i, and $\xi_{i,} \geq 0$ are a safe slack defined by the designer.

Given this consideration, the new multiobjective formulation for the problem 22 may be stated as the minimization of the following objectives:

$$f_1 = B_{stray} = \sqrt{\frac{\sum_{i=1}^{21} |B_{stray,i}|^2}{21}} \tag{13}$$

$$f_2 = \left|\frac{Energy - E_0}{E_0}\right| \tag{14}$$

$$f_3 = \sum_{i=1,2} \{|J_i| + 6.4(|B_{max,i}| + \xi_i) - 54\}^2 \tag{15}$$

Subject to

$$|J_i| + 6.4(|B_{max,i}| + \xi_i - 54 \leq 0 \tag{16}$$

Where $B_{stray,i}$ is the magnetic flux density evaluated in each of the 21 evaluation points for the strayed field along lines a and b (see Fig 3.1). Energy is the stored energy for the current configuration, and $E_0 = 180MJ$. The objective f_2 gives the percentual deviation from the prescribed value of stored energy. The stored energy is evaluated using a finite-element model, whereas the field values are determined directly using the Biot– Savart equation. We have an extra geometric restriction for the eight-parameter variant.

$$R_1 + \frac{h_1}{2} - R_2 + \frac{h_2}{2} \leq 0 \tag{17}$$

that is, the superposition of the coils is not permitted. The restriction for the quench condition is kept, but the third purpose is to find a solution that is close to the quench condition's limit, taking into account the specified level i. In reality, the Pareto solutions obtained contain a variety of operational points from which the best design may be chosen.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The majority of real-world electrical engineering issues needed the optimization of several objective functions with varying restrictions. Deterministic optimization strategies, on the other hand, fail to identify the global optimal solutions to these sorts of problems. Many efforts have been expended in recent years to investigate and develop new stochastic optimal methods, such as the genetic algorithm, differential evolution, tabu search method, cross entropy, simulated annealing, ant colony method, and particle swarm optimization method, which have all been successfully applied to electromagnetic design problems.

This study contributes by proposing several ways of quantum-behaved PSO (QPSO) based on Gaussian distribution for continuous optimization, which are inspired by PSO and quantum mechanics theories. The use of Gaussian sequences in QPSO rather than random sequences with uniform distribution is a powerful method for improving QPSO performance in preventing premature convergence to local optima.

To enhance the position update equation of QPSO, multiple methodologies such as Gaussian, exponential, Cauchy, beta, and other probability distributions methods are utilised to create random numbers and increase the QPSO performance in terms of solution quality and convergence time.

3.2 Quantum Behaved Particle Swarm Optimization using Gaussian mutation

For the stochastic coefficients of PSO, generating random numbers using Gaussian distribution sequences with zero mean and unit variance may provide a good compromise between the probability of having a large number of small amplitudes around the current points (fine tuning) and the probability of having higher amplitudes, which may allow particles to move away from the current point and escape local minima. (Coelho 2010).

The absolute value of a Gaussian probability distribution with zero mean and unit variance is used to create random numbers in this study., i.e., $abs(N(0,1))$. These new QPSO approaches combined with mutation operator are described as follows:

Approach 1- GQPSO: Parameter u is modified by the following equation:

$$\begin{cases} x_i(t+1) = p + \beta \cdot |Mbest_i - x_i(t)| \cdot \ln\left(\frac{1}{G}\right), if\ k\ \geq 0.5 \\ x_i(t+1) = p - \beta \cdot |Mbest_i - x_i(t)| \cdot \ln\left(\frac{1}{G}\right), if\ k < 0.5 \end{cases} \tag{18}$$

where $G = abs(N(0,1))$.

Approach 2 – GQPSO: Parameters c1 and c2 are modified by the following equation:

$$p = \frac{G \cdot p_{i,d} + g \cdot p_{g,d}}{G + g} \tag{19}$$

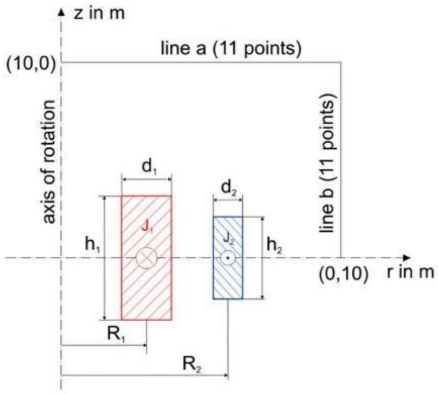
Where $g = abs(N(0,1))$.

Approach 3 – GQPSO: This approach uses Eq. (18) and (19)

3.3 Optimization Strategy

We adopt the TEAM workshop problem 22 of a three-parameter optimization issue involving the setup of a superconducting magnetic energy storage (SMES), but we substitute it with two cross sections of torus coil. SMES arrangement can be built as a torus or a solenoidal coil (Schönwetter et al. 1995). As seen in Fig. 3.1, the TEAM workshop problem is a SMES design optimization.

The system is made up of two concentric coils that transport electricity in opposing



directions.

Figure 3.1: SMES Configuration

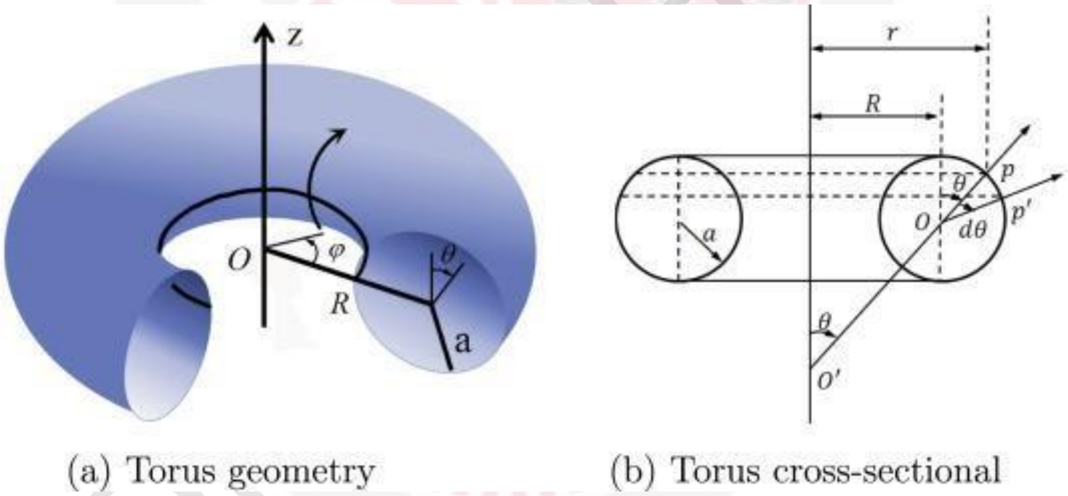


Figure 3.2: Toroidal coil configuration

Fig 3.2(a) shows the geometry of torus in 3dimensional view. R is radius from the center of torus to the center of cross section of it, a is radius inside the cross section area. Fig 3.2(b) is showing how the two cross section of torus is replaced with Fig 3.1. Magnetic field that want to be minimized is located anywhere along the axis (in Fig 3.2(b) denoted as p and p', while Fig 3.3 as x) that always 90 degree with $d\boldsymbol{l}$.

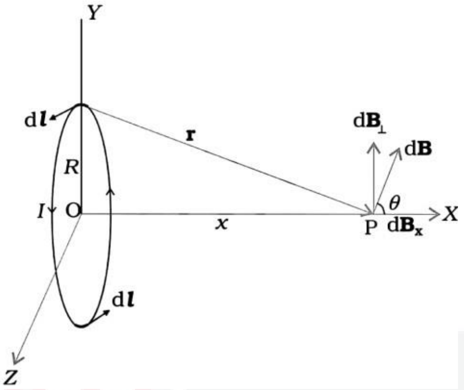


Figure 3.3: Magnetic field of coil

A SMES configuration (Tab 3.1) must be optimised with respect to the following objectives, regardless of the number of parameters: the magnetic field must not violate the quench condition; and the stored energy in the device must be 180 MJ. We set the maximum generation to 50, the swarm size to 20, the dimension to 3, and the c1 and c2 to 2.05.

3.4 Definition of 6 parameter problem

Table 3.1: Geometrical constraint

	R_1 m	R_2 m	r_1 m	r_2 m	J_1 A/m^2	J_2 A/m^2
Min	4	4	2	2	18.3	18.3
max	5	5	3	3	25.5	25.5

3.5 Quench Condition

The superconducting material shall not violate the quench condition, which connects the maximum value of magnetic flux density with the maximum value of current density, as illustrated in Fig 2.3. The critical curve has been approximated by Eq (16).

$$|J| = (-6.4|B| + 54.0)\ A/mm2 \tag{16}$$

3.6 Design Constraint

$$R > r \tag{30}$$

Coils must not overlap, not overlapping itself at origin of axes. Superconductors:

H = 0 inside so no energy inside coils.

3.6.1 Constraint Handling

Approaches that retain solution feasibility, penalty-based methods, methods that clearly discriminate between viable and implausible solutions, and hybrid methods are some of the categories of these methods (Michalewicz & Schoenauer, 1996). Constraints are commonly handled in optimization approaches based on the idea of penalty functions (which penalise unfeasible solutions). That is, one attempts to solve an unconstrained minimization problem in the search space using a modified fitness function, such as:

$$eval(x) = \begin{cases} f(x), & if\ x \in F \\ f(x) + penalty(x), & otherwise \end{cases} \tag{21}$$

where $penalty(x)$ is zero if no constraint is violated, and is positive otherwise. Typically, the penalty function is based on the distance to the nearest solution in the feasible area F or the effort to repair the solution.

The methodology for constraint handling is divided into two steps. The first stage is to identify solutions for decision variables that are inside the user-defined upper (ub) and lower (lb) boundaries, i.e., $x \in [ub, lb]$. A repair rule is implemented if a lower bound or an upper bound constraint is not fulfilled, as defined by Eqs (22) and (23), respectively:

$$x_i = x_i + rand[0,1] \cdot \{ub(x_i) - lb(x_i)\} \tag{22}$$

$$x_i = x_i - rand[0,1] \cdot \{ub(x_i) - lb(x_i)\} \tag{23}$$

Where $rand[0,1]$ is a uniformly distributed random value between 0 and 1. In the second step decision variables are considered inequalities ($g_i(x) \leq 0$). In this work we minimize the objective function, thus the objective function equation is rewritten as:

$$eval(x) = \begin{cases} f(x), & if\ g_i(x) \leq 0 \\ f(x) + r \cdot q \cdot \sum_{i=1} g_i(x), & if\, g_i(x) > 0 \end{cases} \tag{24}$$

where q is a positive constant (arbitrarily set to 1000) and r is the number of constraints $g_i(x)$ that were not satisfied.

TEAM Problem 22 benchmark can be solved semianalytically by Biot-Savart's law. (Alotto et al. 1996)

$$B = \frac{\mu_0 I r^2}{2(R^2 + r^2)^{\frac{3}{2}}} \tag{25}$$

In this study, a parameter optimization technique based on the particle swarm algorithm is described utilising the MATLAB co-simulation method. The flow chart for this procedure is shown in Fig.3.4.

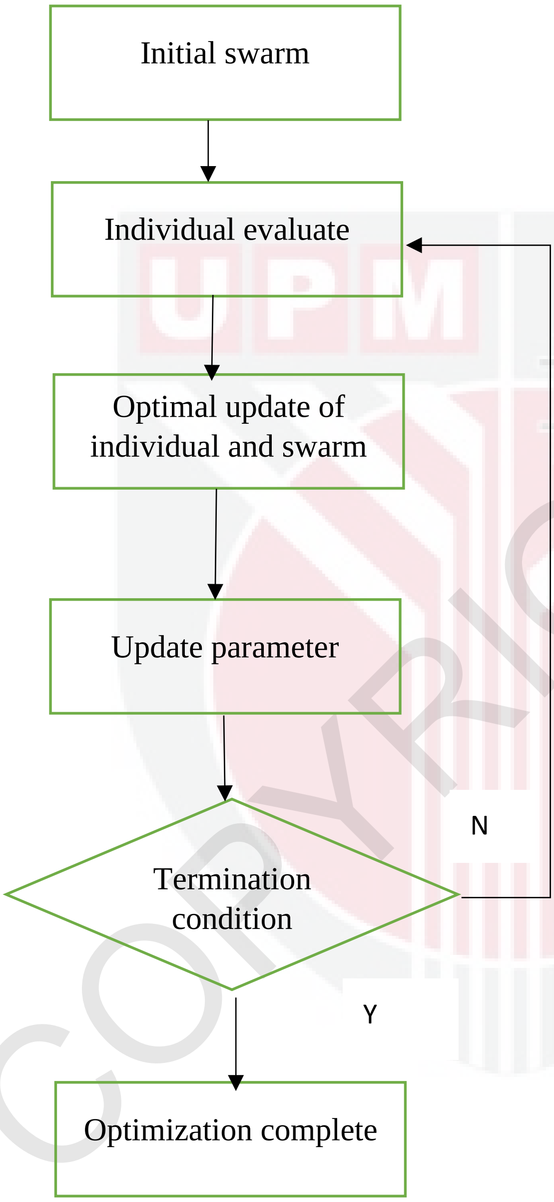


Figure 3.4: Flow chart of energy storage ring parameters optimization.

CHAPTER 4

RESULTS

4.1 Numerical results and discussion

The QPSO's performance was evaluated using the case studies provided in the preceding section. Method were implemented using MATLAB R2021a which was installed on a PC with a Windows 10 Pro operating system and Intel(R) Core(TM) i57200U CPU @ 2.50GHz 2.70 GHz.

The problem of SMES optimization using benchmark TEAM Problem 22 has already been solved by researchers (PG Alotto, Baumgartner, and Freschi 2008). Some researchers also has employed an approach of improved evolutionary programming, including (Rehman et al. 2018) who added some mutation operation to the particle with global best position, and (Liu, Wang, and Yang 2015) who modified PSO with a dynamic inertia weight and an adaptive mutation operator.

Simulations are conducted to optimize the parameter of storage ring and calculate the magnetic field while keeping the energy inside the coil and under the quench. Performances are then assessed on the basis of the best fitness values and the iteration. Results of convergence behaviour of QPSO are reported in Fig 4.1.

As a result of these numerical results, one may compare the performance of evaluated stochastic techniques in terms of both solution quality and convergence speed (number of iterations).

Tab 4.1 show the result of optimal parameter from the runned program. The patch graph can be changed due to the result of using random number of Gaussian distribution sequences in GQPSO.

Table 4.1: Result of QPSO approach

Design variables	Parameter	QPSO
x_1	R_1, R_2	3.37151
x_2	r_1, r_2	1.10253
x_3	$I_{1,}, I_2$	15.8508
fx	Eq(25)	0.012059

4.2 Quench Condition

We calculate the quench by the average of the parameter which R_1, R_2 is $4.5m$, r_1, r_2 is $2.5m$ and $I_{1,}$, I_2 is 21.9 A. The current density of the toroidal design using equation

$$J = \frac{I}{A} \quad (26)$$

Is equal to $\approx 1.11538 A/m^2$. While the current density using quench condition from Eq(16) give result equal to ≈ 54 A/m^2. Thus, this optimization is not violet the quench condition and assure the superconductivity state.

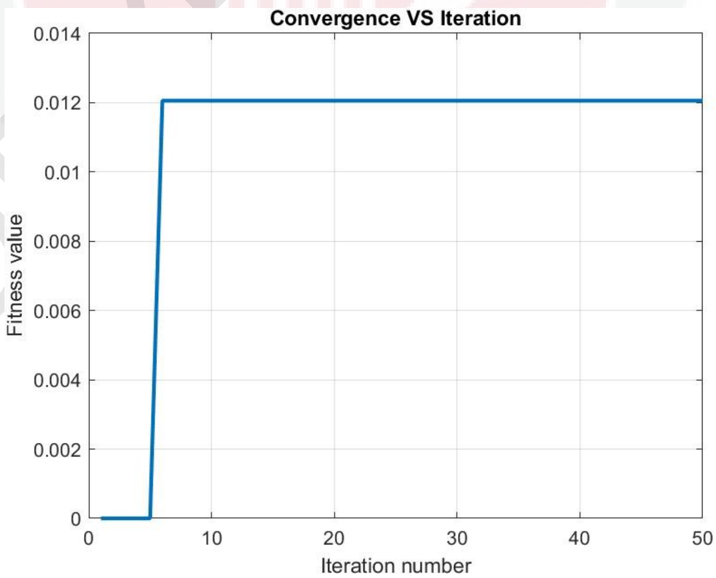


Figure 4.1: QPSO behaviour

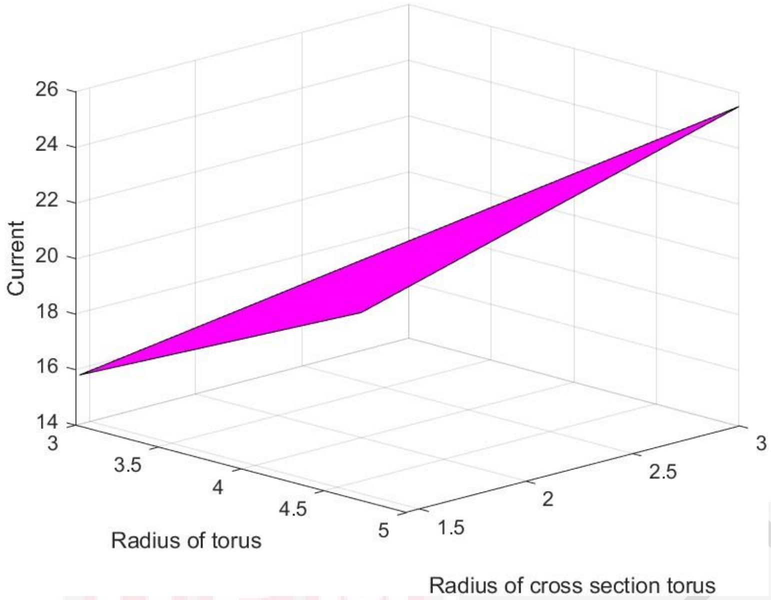


Figure 4.2: Optimum parameter gain from QPSO approach

CHAPTER 5

CONCLUSION

5.1 Conclusion

In this paper, QPSO approaches applied to solve SMES optimization benchmark TEAM Problem 22. Originally the benchmark was designed with two rectangular coils then in this studies, it was replaced with two cross section of toroidal coil as new geometry. The possibilities of exploring the QPSO efficiency combined with Gaussian distribution sequences are successfully presented, as illustrated by the case studies. The simulation results from 50 runs presented in this paper demonstrate that the magnetic field can be calculate with optimize the parameter while keeping the given energy and not violet the quench condition. GQPSO in terms of convergence, the simulation results can show the effectiveness between other stochastic optimization algorithm if want to make comparison. Objective (3) will be carry as future work because it is multiobjective problem and need to mapped into single objective function which require more study about the configuration.

5.2 Limitation of Study

When the program wants to be conducted, limitations occurred: implementation of data sample and lack of previous study in the research area. Because of the lack of substantial expertise in primary data collecting, there is a good likelihood that the nature of the data collection method's implementation is faulty. And there are only little prior research related to the topic and any for evolving research problem. So addressing the research problem, it not able to find many. A literature review is an important aspect of any research project since it aids in determining the breadth of previous work in the field.

5.3 Recommendation

The aim of future works is to investigate the better performance of toroid design by comparing with benchmark using same iteration, population and QPSO parameters. Furthermore, use QPSO for optimization in control systems, reliability engineering, and electric power systems. Also, others relevant studies can be realized, such as: (i) comparative analysis of several approaches of QPSO based on simulated annealing local search, and (ii) design and test of adaptive penalty functions for constrained problems.

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