Coupling of 3D Analytical Calculation and PSO for the Identification of Magnet Parameters used in Magnetic Separation

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Abstract — In this work, the identification of the residual magnetic flux density of NdFeB permanent magnet, used in a drum magnetic separator, is performed. This identification problem has been formulated as an inverse optimization problem and solved using the Particle Swarm Optimization (PSO) method. For fast calculations, flux densities are computed using a 3D analytical method and the obtained results are compared with measurements.

Index Terms — 3D analytical solution, inverse problem, magnetic separation, parameters identification, Particle Swarm Optimization, permanent magnet.

I. INTRODUCTION

In magnetic separation applications, the efficiency of the separation depends strongly upon the configuration of the applied magnetic field [1-4]. To design a reliable magnetic separator both the geometrical and magnetic specifications of the field generator must be accurately known.

The identification problem in physics devices is largely treated. In [5] the authors presented a simultaneous identification and control of adaptive torque of permanent magnet synchronous machines. In [6] a multiple object positioning and identification method based on the magnetic tracking system was proposed for tracking of minimally invasive medical devices inside human body, such as wireless capsule endoscope. In electrical machine domain, an inverse problem coupled with an analytical model was used for the identification of demagnetization faults in axial flux permanent magnet synchronous machines [7]. Zhe et al. [8] proposed an identification procedure for an Active Magnetic Bearing System (AMBS), which makes it possible to estimate the unknown parameters and to establish the model of transfer function matrix of the AMB system.

The aim of this paper is the identification of the three components of the residual magnetic flux density $\vec{B}_r(B_{rx}, B_{ry}, B_{rz})$ of an NdFeB permanent magnet constituting a rectangular bar with size $1.2\times1\times10\text{cm}^3$ used to realize a drum magnetic separator (see Fig. 1). For that, an inverse optimization problem is formulated and then solved where the objective function is the Mean Squared Error (MSE) between measured and computed values of the magnetic flux density in three different locations in the permanent magnet.

In the field of electromagnetics, several optimization methods have been used to solve different problems as reported in [9-17]. In this paper, the Particle Swarm Optimization (PSO) method has been used to solve the defined problem and the Most Valuable Player Algorithm (MVPA) is used for comparison purposes.

An experimental setup has been developed to measure the magnetic flux density of the permanent magnet. This last one has a parallelepiped shape and a rigid magnetization, this allows to use a 3D (in Cartesian coordinates) analytical integration method [18-19]. Such a solution is more accurate and faster than numerical ones which will make the optimization process faster.

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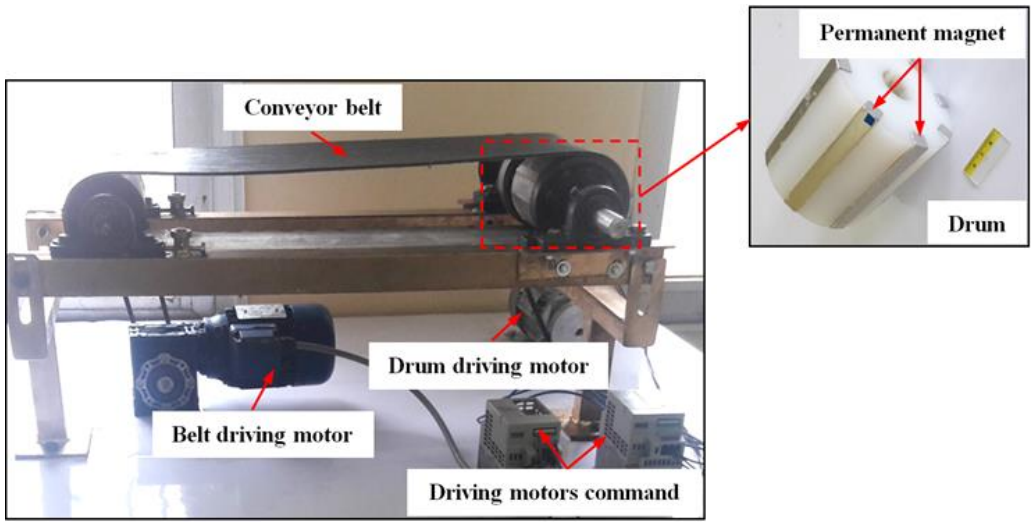


Fig. 1. Experimental setup of the magnetic drum separator.

II. GENERATED MAGNETIC FIELD AND LOCATION OF MEASUREMENT FOR OPTIMIZATION

To know the accurate configuration of the magnetic field generated by the used permanent magnet, measurements have been performed. For this, we have realized and used the experimental test bench presented in Fig. 2.

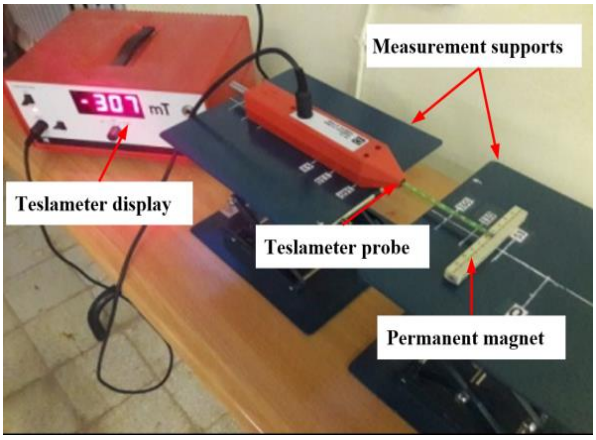


Fig. 2. Experimental setup for measuring the magnetic field.

To define the number of measuring locations required for the optimization process, we have measured and analyzed the magnetic flux density on all the faces of the permanent magnet. To show the nature of the variations of the magnetic flux density on the magnet surfaces, we present the variation of the measured magnetic flux density along the length of two lines situated in significant surfaces oriented in the $\vec{y}$ and $\vec{z}$ directions (see Fig. 3). The line 2 is chosen near the corner of the permanent magnet because along the middle line of this surface the magnetic flux density (B_y) is zero.

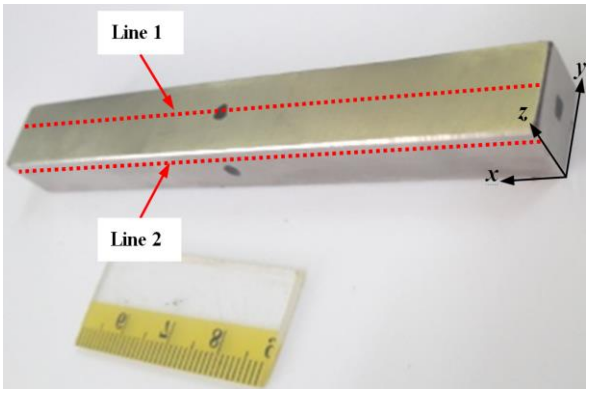
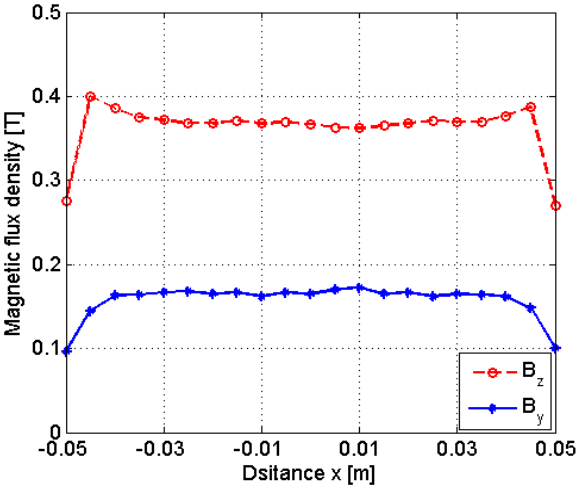
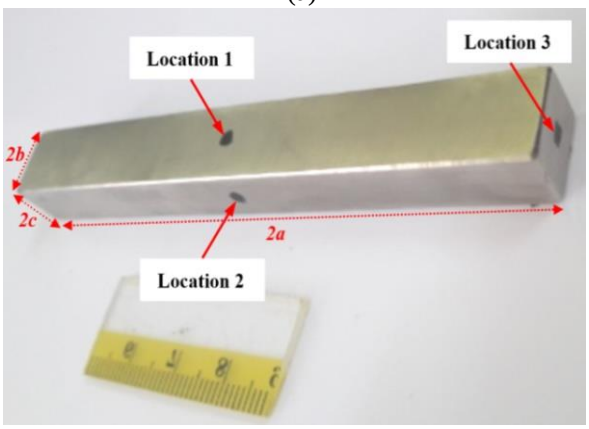


Fig. 3. Lines where the variation of the magnetic flux density is measured.

As shown in Fig. 4 (a), the magnetic flux density is almost constant along the length of the considered line of the significant surfaces of the permanent magnet except at the borders. Using this result along with the fact that each two opposite surfaces of the permanent magnet have opposite magnetic polarities, measuring locations for the optimization are reduced to only three locations located at the center of the three surfaces (see Fig. 4 (b).



(a)



(b)

Fig. 4. (a) Variation of the magnetic flux density along the considered lines, and (b) the three measuring locations for the optimization process.

III. PROBLEM FORMULATION

As aforesaid, the identification problem treated in this paper has been formulated as an inverse optimization problem where the design variables are the three components of the residual magnetic flux density B_{rx}, B_{ry} and B_{rz} of the permanent magnet bar and the objective function is MSE between measured and computed values at three different locations. The objective function can be expressed as follows [20]:

$$F = \frac{1}{2}\sum_{i=1}^{3}\left(B_{mi} - B_{ci}\right)^2, \tag{1}$$

where B_{mi} and B_{ci} are respectively the measured and computed values at the locations $i\ (i = 1, 2, 3)$. In (1), the computed values B_{ci} are function of the three researched parameters $B_{ci} = f\left(B_{rx}, B_{ry}, B_{rz}\right)$.

To compute the quantities B_{ci} we have used the 3D analytical solution given by [21-22]:

$$\begin{bmatrix} B_x \\ B_y \\ B_z \end{bmatrix} = \frac{1}{4\pi}\sum_{i=0}^{1}\sum_{j=0}^{1}\sum_{k=0}^{1}(-1)^{i+j+k}\begin{bmatrix} tg^{-1}\left(\frac{VW}{rU}\right) & \ln(r-W) & \ln(r-V) \\ \ln(r-W) & tg^{-1}\left(\frac{WU}{rV}\right) & \ln(r-U) \\ \ln(r-V) & \ln(r-U) & tg^{-1}\left(\frac{UV}{rW}\right) \end{bmatrix}\begin{bmatrix} B_{rx} \\ B_{ry} \\ B_{rz} \end{bmatrix}. \tag{2}$$

The intermediary variables U, V and W are given by [21-22]:

$$\begin{cases} U = x - (-1)^i a,\ V = y - (-1)^j b,\ W = z - (-1)^k c \\ r = \sqrt{U^2 + V^2 + W^2} \end{cases}. \tag{3}$$

The steps followed to obtain expression (2) are developed in the Appendix.

It is worth to mention that, the choice of three locations to measure the magnetic flux density (the perpendicular component at each face) has considerably reduced the computational time for the optimization process.

IV. OPTIMIZATION METHOD AND OBTAINED RESULTS

To minimize the objective function, the PSO method has been applied [23]. It is a population-based stochastic algorithm and one of the global optimization methods, it simulates the migration and aggregation of animals, such as birds, fishes and bees when they seek for food. The basic form of the PSO algorithm is based on the evolution or movement of a population (called a swarm) of candidate solutions (called particles) in the search space. Each one of these particles has its position, velocity and a fitness value that is determined by an optimization function. The optimization is performed in terms of the objective function where each particle knows its best position obtained individually so far and is called the Personal Best (P_{pbest}). In the same way, the other particles know what is the best position obtained collectively so far and is called the Global Best (P_{gbest}). Each particle updates its velocity and position at each iteration by using the mathematical models given by [24].

$$v_m(t+1) = \omega\, v_m(t) + c_1 r_1\left(P_{pbest}(t) - x_m(t)\right) + c_2 r_2\left(P_{gbest}(t) - x_m(t)\right), \tag{4}$$

$$x_m(t+1) = x_m(t) + v_m(t+1), \tag{5}$$

where m is the particle number, v and x are the particle velocity and position, respectively, c_1 is the cognitive coefficient, c_2 is the social coefficient, r is a random values in the interval [0, 1] and ω is the inertia weight who ensures that the particle swarm can search from the whole search space in the early iterations and converge in later iterations. The PSO method used in this paper is implemented according to the pseudo code given in Algorithm 1 [25].

Algorithm 1: Pseudocode of the PSO method

Input: Problem Size; Population Size
Output: P_{gbest}
Population ← ∅
P_{gbest} ← ∅
  for i=1: population Size
    $P_{velocity}$ ← Random Velocity
    $P_{position}$ ← Random Position
    P_{pbest} ← $P_{position}$
    if cost(P_{pbest}) ≤ cost(P_{gbest})
      P_{gbest} ← P_{pbest}
    end
  end
  while (Stop condition)
    for each P ∈ Population
    $P_{velocity}$ ←Update Velocity($P_{velocity}$, P_{gbest}, P_{pbest})
    $P_{position}$ ← Update Position($P_{position}$, $P_{velocity}$)
    if cost($P_{position}$) ≤ cost(P_{pbest})
      P_{pbest} ← $P_{position}$
      if cost(P_{pbest}) ≤ cost(P_{gbest})
        P_{gbest} ← P_{pbest}
      end
    end
    end
  end
return P_{gbest}

In this paper, he PSO method has been programmed using the commercial MATLAB software and run on a computer with Intel(R) Xeon(R) CPU E5-1620 v2 @ 3.70 GHz Processor and 8.00 GO-RAM under professional windows 7 environment. The stopping criterion was chosen as $\varepsilon = 1\times10^{-9}$ so that the iteration stopped when $F \le \varepsilon$. The tuning parameters used for the PSO algorithm are listed in Table 1.

Table 1: PSO tuning parameters

Parameters	Values
Population Size	40
Cognitive coefficient c_1	-0.6504
Social coefficient both c_2	2.2073
Inertia weight ω	-0.4349
Range of the researched parameters	[-1.3 1.3]

The optimal design variables found after 27 iterations are displayed in Table 2.

Table 2: Optimal values found after 27 iterations

Parameters	Values
B_{rx}(T)	-2.27×10^{-5}
B_{ry}(T)	1.39×10^{-5}
B_{rz}(T)	1.1066
F	1.94×10^{-10}
$t(s)$	0.1989

The results of Table 2 show that the dominant component of the residual flux density is B_{rz} which signifies that the magnetization of the permanent magnet is oriented in the z-axis direction. To verify the obtained results, we have computed the magnetic flux density along the lines of Fig. 3. The comparison between the computed and measured values is presented in Fig. 5.

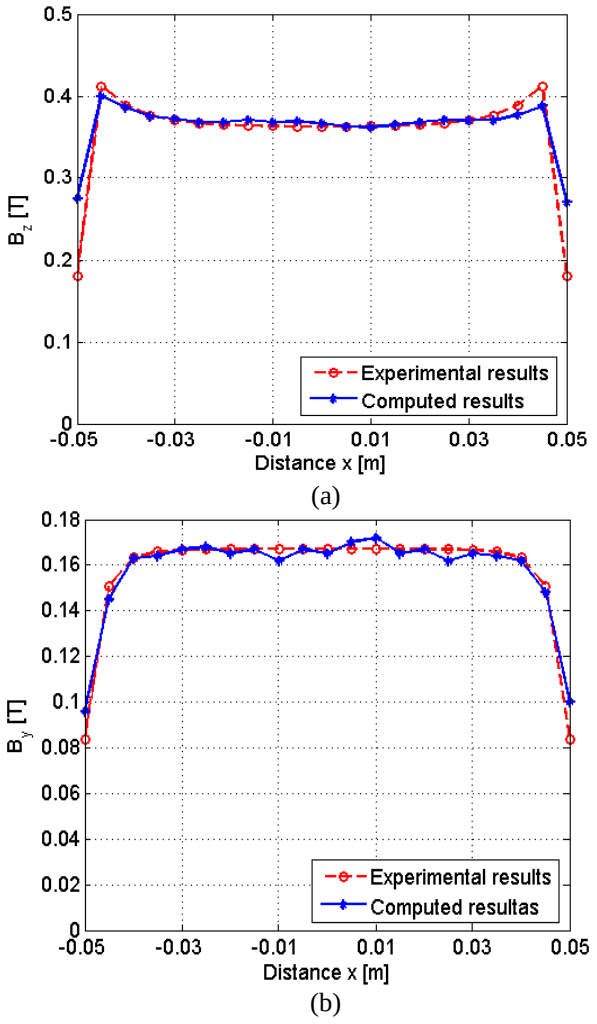


Fig. 5. Variation of the magnetic flux density related to the identified parameters. (a) Variation along the length of the line 1, and (b) variation along the length of the line 2.

Figure 5 shows that the measured and computed results are very close, which validates the reliability of the developed computing codes and the obtained results.

For a global verification of the achieved optimization, we have compared the results obtained by the PSO with those obtained by the Multi Valuable Player Algorithm (MVPA) method.

The MVPA is a recently developed algorithm inspired from sport [16]. It is a very competitive algorithm compared with other optimization algorithms as proved in [26] and [27]. The pseudo code of the MVPA is given in Algorithm 2 and the main steps are detailed bellow. Like other population-based metaheuristics, the MVPA starts by generating a population of players inside the search space following a random distribution. These players are regrouped into teams (line 3). Then the algorithm will iterate 'MaxNFix' times trying to evolve the population to find the optimal solution. In each iteration, a loop on all teams selects a first team called TEAMi. The players of this team compete to determine to best player (Franchise Player) of this team and the population is updated accordingly (line 8). This first phase is called the 'individual competition phase'. In the second competition phases called 'team competition phase', a second team called TEAMj is randomly selected among the leagues' teams. TEAMi and TEAMj play against each other to determine the wining team. The population is updated according to the outcome of this matchup (lines 9-13). Once the competition phase is completed the players are checked to see if there is any player outside the search space. In such case, this player is brought back to the search space (line 14). In order to improve the performance of the MVPA three steps have to be performed which are 'application of greediness', 'application of elitism' and 'remove duplicates'. In the first step, a player is updated only if his new fitness is better than the old one. In the second step, some of the worst players are replaced by some of the best players. In the third step duplicate players are removed and changed by new ones.

In the pseudocode of the MVPA, the inputs are the function (ObjFunction), the number of design variables (ProblmSize), the number of players which is equivalent to the population size (PlayersSize), the number of teams in the league (TeamsSize) and the maximum number of fixtures which is equivalent to the maximum number of iterations (MaxNfix). The output of the algorithm is the leage's MVP which is the best solution obtained.

To estimate the speed of convergence of the two applied methods, Fig. 6 plots the evolution of the objective function versus the number of iterations.

Algorithm 2: Pseudocode of the MVPA method

1 **Inputs:** ObjFunction (objective function), ProblemSize (dimension of the problem), PlayersSize (number of players), TeamsSize (number of teams) and MaxNFix (maximum number of fixtures)

2 **Output**: MVP

3 Initialization

4 **for** fixture=1:MaxNFix

5 **for** i=1:TeamsSize

6 $\mathrm{TEAM_i}$ =Select the team number i from the league's teams

7 $\mathrm{TEAM_j}$ = Randomly select another team j from the league's teams where j≠i

8 $\mathrm{TEAM_i} = \mathrm{TEAM_i} + \mathrm{rand} \times (\mathrm{FranchisePlayer_i} - \mathrm{TEAM_i}) + 2 \times \mathrm{rand} \times (\mathrm{MVP} - \mathrm{TEAM_i})$

9 **if** $\mathrm{TEAM_i}$wins against $\mathrm{TEAM_j}$

10 $\mathrm{TEAM_i} = \mathrm{TEAM_i} + \mathrm{rand} \times (\mathrm{TEAM_i} - \mathrm{FranchisePlayer_j})$

11 **else**

12 $\mathrm{TEAM_i} = \mathrm{TEAM_i} + \mathrm{rand} \times (\mathrm{FranchisePlayer_j} - \mathrm{TEAM_i})$

13 **end**

14 Check if there are players outside the search space

15 **end**

16 Application of greediness

17 Application of elitism

18 Remove duplicates

19 **end for**

A comparison between the results obtained by PSO and those obtained by MVPA method is shown in Table 3.

Table 3: Optimal values of the researched parameters obtained by the two methods

Parameters	**PSO**	**MVPA**
B_{rx} (T)	-2.27×10^{-5}	-1.07×10^{-4}
B_{ry} (T)	1.39×10^{-5}	-1.34×10^{-4}
B_{rz} (T)	1.1066	1.1069
F	1.94×10^{-10}	7.67×10^{-10}
t (s)	0.1989	0.2505
Iteration's number	27	15

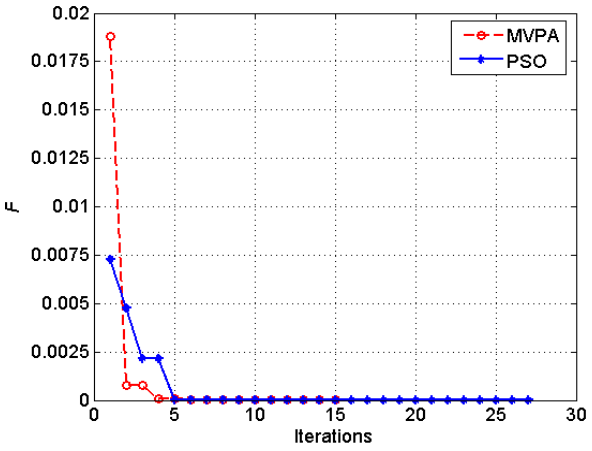


Fig. 6. Evolutions of the objective function as a function of computing iterations.

The comparison between the obtained results of the Table 3 and Fig. 6 show that the two applied optimization methods have given the same values of the three researched parameters corresponding to the three components of the residual magnetic flux density.

The obtained results show clearly that the MVPA converges quickly but the PSO algorithm performs better in terms of running time.

V. CONCLUSION

In this work, developed for a magnetic separation study, a methodology for NdFeB permanent magnet parameters identification based on the resolution of an inverse problem has been presented. In such methodology, the PSO method is combined with 3D analytical solution, which has given a good accuracy and a low processing cost. The results of the analytical solution have been validated by comparison with measurements. For a global verification of the achieved optimization, we have compared the obtained results by the PSO with those obtained by the Multi Valuable Player Algorithm (MVPA) method. The comparison shows that the two applied methods have given the same optimal results. However, the PSO method presents better performances in terms of running time.

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APPENDIX

Analytical calculation of magnetic flux density created by a magnet

Based on the conventional equivalent magnetic charge method, for parallel uniform magnetized magnet in *z* direction, the magnetization effect can be represented by two parallel magnetic charge surfaces (Colombian approach) on the sides of the permanent magnet which their normal is collinear with the supposed magnetization direction [28].

An assumed rigid and uniform magnetization can be replaced by a distribution of magnetic poles. The density of such poles distribution is defined by [29]:

$$\sigma = \vec{M}.\vec{n} = \frac{\vec{B}_r}{\mu_0}.\vec{n}. \tag{6}$$

Let us consider the rectangular surface $2a \times 2b$ having a uniform pole density σ (Fig. 7).

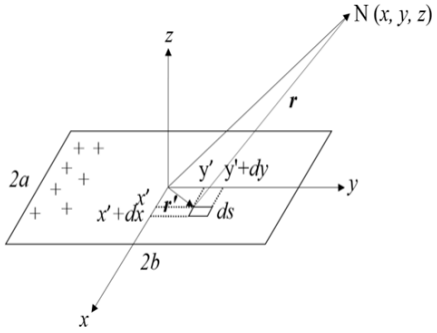

Fig. 7. Geometrical illustration for the potential and the magnetic field calculation.

The magnetic scalar potential *V* in a point N is given by [21-22]:

$$V = \frac{1}{4\pi}\iint_S \frac{M.ds}{\|\vec{r}-\vec{r}'\|}. \tag{7}$$

Depending on the residual magnetic flux density, the expression (7) can be written as:

$$V = \frac{1}{4\pi\mu_0}\iint_S \frac{B_r.ds}{\|\vec{r}-\vec{r}'\|}. \tag{8}$$

In Cartesian coordinates system, (8) can be written as:

$$V = \frac{B_r}{4\pi\mu_0}\int_{-b}^{b} dy' \int_{-a}^{a} \frac{1}{\sqrt{(x'-x)^2+(y'-y)^2+z^2}}dx'. \tag{9}$$

After two analytical integrations, we obtain:

$$V = \frac{B_r}{4\pi\mu_0}\sum_{i=0}^{1}\sum_{j=0}^{1}(-1)^{i+j}\left(-U\ln(r-V)-V\ln(r-U)-W.tg^{-1}\left(\frac{UV}{rW}\right)\right), \tag{10}$$

$$\begin{cases} U = x-(-1)^i a\ ,\ V = y-(-1)^j b\ ,\ W = z \\ r = \sqrt{U^2+V^2+W^2} \end{cases}. \tag{11}$$

The magnetic field can be calculated by deriving the scalar potential expression, which leads to:

$$\vec{H} = \frac{Br}{4\pi\mu_0}\sum_{i=0}^{1}\sum_{j=0}^{1}(-1)^{i+j}\begin{pmatrix} \ln(r-V) \\ \ln(r-U) \\ tg^{-1}\left(\frac{UV}{Wr}\right) \end{pmatrix}. \tag{12}$$

So, the magnetic flux density is given by:

$$\vec{B} = \frac{B_r}{4\pi} \sum_{i=0}^{1} \sum_{j=0}^{1} (-1)^{i+j} \begin{pmatrix} \ln(r-V) \\ \ln(r-U) \\ tg^{-1}\left(\frac{UV}{Wr}\right) \end{pmatrix}. \quad (13)$$

For a cubical magnet in which the magnetization is collinear with *z* direction, (see Fig. 8), the magnetic flux density can be determined from the upper and the lower charged surfaces.

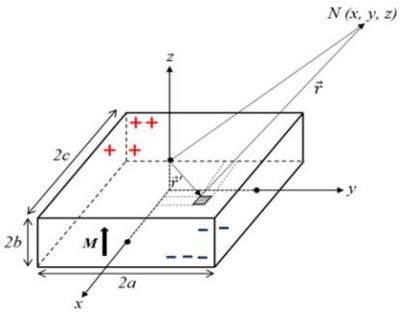

Fig. 8. Magnetic field created by a cuboidal permanent magnet.

In this case, comparing also to (equation 13), the magnetic flux density will be:

$$\vec{B} = \frac{Br}{4\pi} \sum_{i=0}^{1} \sum_{j=0}^{1} \sum_{k=0}^{1} (-1)^{i+j+k} \begin{pmatrix} \ln(r-V) \\ \ln(r-U) \\ tg^{-1}\left(\frac{UV}{Wr}\right) \end{pmatrix}. \quad (14)$$

The intermediary variables become:

$$\begin{cases} U = x-(-1)^i a\,,\ V = y-(-1)^j b\,,\ W = z-(-1)^k c \\ r = \sqrt{U^{\,2}+V^{\,2}+W^{\,2}} \end{cases}. \quad (15)$$

For a permanent magnet magnetization oriented randomly in space, the global magnetization is the superposition of the three components as shown in Fig. 9:

$$\vec{M} = M_x\vec{i} + M_y\vec{j} + M_z\vec{k}. \quad (16)$$

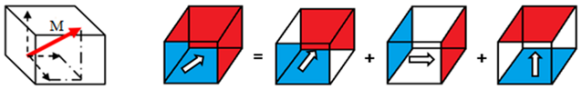

Fig. 9. Decomposition of a randomly oriented magnetization in a permanent magnet [22].

Then, the computation of the total components of is deduced as follows:

$$\vec{B} = \vec{B}_x + \vec{B}_y + \vec{B}_z, \quad (17)$$

According to the result given by *z* axis-oriented magnetization (7 to 13), the total *B* resulting from the inclined magnetization is given by a simple permutation of analytic formulas for the two other directions of magnetization (*x* axis and *y* axis). So, we can write:

$$\vec{B} = \frac{1}{4\pi} \sum_{i=0}^{1} \sum_{j=0}^{1} \sum_{k=0}^{1} (-1)^{i+j+k} \begin{bmatrix} B_{rx} tg^{-1}\left(\frac{WV}{rU}\right) + B_{ry}\ln(r-W) + B_{rz}\ln(r-V) \\ B_{rx}\ln(r-W) + B_{ry} tg^{-1}\left(\frac{WU}{rV}\right) + B_{rz}\ln(r-U) \\ B_{rx}\ln(r-V) + B_{ry}\ln(r-U) + B_{rz} tg^{-1}\left(\frac{VU}{rW}\right) \end{bmatrix}, \quad (18)$$

In other manner, we can write the magnetic flux density components as:

$$\begin{bmatrix} B_x \\ B_y \\ B_z \end{bmatrix} = \frac{1}{4\pi} \sum_{i=0}^{1} \sum_{j=0}^{1} \sum_{k=0}^{1} (-1)^{i+j+k} \begin{bmatrix} tg^{-1}\left(\frac{VW}{rU}\right) & \ln(r-W) & \ln(r-V) \\ \ln(r-W) & tg^{-1}\left(\frac{WU}{rV}\right) & \ln(r-U) \\ \ln(r-V) & \ln(r-U) & tg^{-1}\left(\frac{UV}{rW}\right) \end{bmatrix} \begin{bmatrix} B_{rx} \\ B_{ry} \\ B_{rz} \end{bmatrix}, \quad (19)$$

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