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Mathematical Modeling (Buckingham's π Theorem) and Optimization Technique on Mechanically Alloyed Nanocomposite Materials

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Abstract: ***This research work is focused to develop and investigate the mathematical linear and non-linear modelling techniques for mechanically alloyed nanocomposites materials. These conventional and non-conventional artificial intelligent models could predict the both physical and mechanical properties of some nanocomposites materials. The conventional techniques such as dimensional analysis using Buckingham π-theory, regression analysis and its hybrid approach; and non-conventional approaches like neural networks, fuzzy theory and adaptive fuzzy theory have addressed through this research work. The most significant input parameters which would affect the mechanical alloying processes, namely, milling time (t, min), ball-to-powder ratio (B), milling speed (N, rpm), ball size (D, mm), percentage of reinforcement (R, %) sintering temperature (T, K), sintering time (ts, min) and consolidation pressure (P, MPa) can be used for the various models. The various responses as physical and mechanical properties to be used are crystallite size (d, nm), bulk hardness (H, MPa), bulk density (ρ, kg/m*** ^{3}***), tensile strength (*** σ_y***, MPa), matrix particle size (Z, µm), compressive strength (*** σ_u***, MPa), and percentage of elongation (e, %). Through this research work, we can select an optimum input parameter as per our required output properties, predicting the physical and mechanical behavior of nanocomposites and select the best linear & non-linear methods.***

Keywords: ***Nanocomposites; Mechanical Alloying; Mathematical modeling; Non-Traditional techniques.***

I. INTRODUCTION

In modern industry, the research community are focusing their work towards nanomaterials / nanocomposites and the way to synthesis and controlling of microstructure related to mechanical applications which would mainly affect the performance of any components / products [1]. There are several techniques available towards the processing of nanomaterials / nanocomposites in which solid state processing route using high-energy ball milling technique is playing major role as this process can be used to manufacture the nanomaterials nanocomposites in large industrial scale [2]. Based on our requirements, the synthesized materials could be in the form of amorphous, and or supersaturated, and or nanostructured, and or nanocomposites powder particle [3-5]. The process of mechanical alloying is one of stochastic in nature which performance would main depends on selection of proper input and output process parameters. Therefore, this process could involve complicated modeling system which needs to be explored clearly to the research community. The developed models could predict the system behavior exactly that can be well suited in some manufacturing industries [4]. Benjamin and Volin [6] have developed a mathematical modeling first for the manufacturing of Cr-Fe alloy via mechanical alloying technique. They have found that the grain refinement had mainly depend on the function of logarithmic time, the mechanical energy input and strain hardening effect on the materials being synthesized. In addition, several physical models which includes mechanistic models, thermodynamic models, microstructure based kinetic models, some models related to atomistic level and milling mapping models [4] have been recently studied and investigated by the research community. However, still, many input parameters which affect the mechanical alloying processes have not been included in the models and there is a lack in the model related to deformation behavior of nanomaterials / nanocomposites through mechanical alloying route.

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II. MODELING APPROACH

Advanced materials processing of nanocomposites through solid state processing of mechanical alloying is involving more number of process parameters which urges effort towards the development of various modeling and optimization techniques. This research is aimed to address the various linear/non-linear mathematical methods such as dimensional analysis using Buckingham π-theory, regression analysis and its hybrid approach; other non-traditional modeling techniques such as neural networks, fuzzy theory and adaptive neuro fuzzy theory. The schematic of present research is shown in Fig.1.

The dimensions of the input and output variables are also illustrated in Table 1.

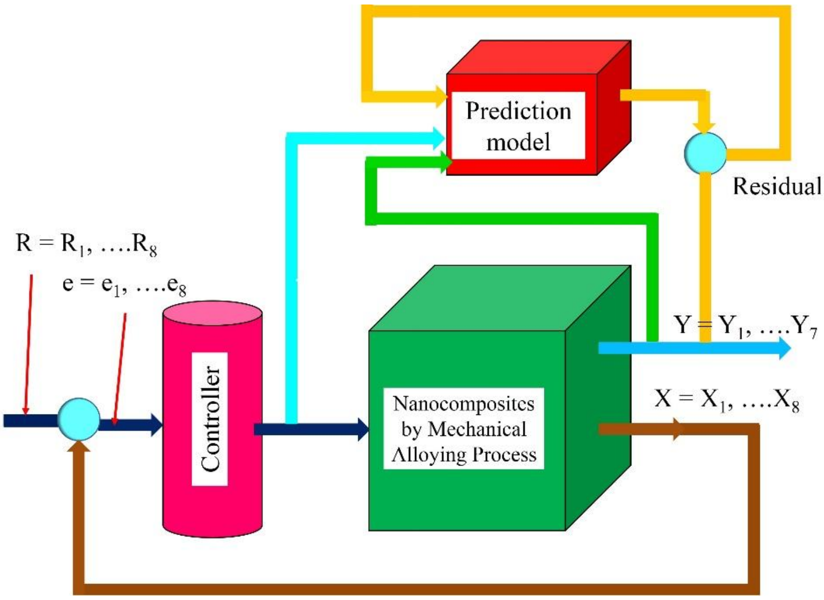

Fig. 1. The schematic

Legend

Input Process Parameters

X_1 = Milling time (t, min)
X_2 = Ball-to-powder ratio (B)
X_3 = Milling speed (N, rpm)
X_4 = Ball size (D, mm)
X_5 = Percentage of reinforcement (R, %)
X_6 = Sintering temperature (T, K)
X_7 = Sintering time (ts, min)
X_8 = Consolidation pressure (P, MPa)

Output Responses

Y_1 = Crystallite size (d, nm)
Y_2 = Bulk hardness (H, MPa)
Y_3 = Bulk density (ρ, kg/m^3)
Y_4 = Tensile strength (σ_y, MPa)
Y_5 = Matrix particle size (Z, μm)
Y_6 = Compressive strength (σ_u, MPa)
Y_7 = Percentage of elongation (e, %)

Legend

R_1 = Reference of Milling time
R_2 = Reference of Ball-to-powder ratio
R_3 = Reference of Milling speed
R_4 = Reference of Ball size
R_5 = Reference of Percentage of reinforcement
R_6 = Reference of Sintering temperature
R_7 = Reference of Sintering time
R_8 = Reference of Consolidation pressure

e_1 = Error between R_1 and Milling time
e_2 = Error between R_2 and Ball-to-powder ratio
e_3 = Error between R_3 and Milling speed
e_4 = Error between R_4 and Ball size
e_5 = Error between R_5 and Percentage of reinforcement
e_6 = Error between R_6 and Sintering temperature
e_7 = Error between R_7 and Sintering time
e_8 = Error between R_8 and Consolidation pressure

diagram showing the implementation of modeling approach for predicting the system behavior

A. Modeling using dimensional analysis of Buckingham's π− theorem

The physical quantities which affect the system behavior responses can be modelled by dimensional analysis which is also one of a novel mathematical method. Using this method, the experimental work can be modeled and then the system behavior can be predicted. These would establish the relationship between the controllable processing parameters and the physical properties of materials. It can be developed based on some assumption which gives a better solution in terms of dimensional equation. The definition of Buckingham π theorem demonstrates the linking of all the process variables into number of π terms which are dimensionless quantities [7, 8]. The mass (M), length (L), time (T), and temperature (θ) are the fundamental dimensionless quantities. Here, total variables are 8 (i.e. n) and fundamental dimensions are 4 (i.e. r) so that there will be 4[i.e. (n - r)] π terms.

Hence, the relationship of π-term can be written as:
Dimensionless equation for crystallite size (d) is

$$d = f\left(t,\ B,\ N,\ D,\ R,\ T,\ t_s,\ P\right) \tag{1}$$

Therefore, functional relationship for π term can be expressed as

$$g\left(\pi_1, \pi_2, \pi_3\right) \tag{2}$$

$$\pi_1 = t^{a1} B^{b1} N^{c1} D^{d1} R^{e1} d \tag{3}$$

$$\pi_2 = t^{a2} B^{b2} N^{c2} D^{d2} R^{e2} t_s \tag{4}$$

$$\pi_3 = t^{a3} B^{b3} N^{c3} D^{d3} R^{e3} P \tag{5}$$

$$\pi_4 = t^{a4} B^{b4} N^{c4} D^{d4} R^{e4} T \tag{6}$$

Dimensionless equation for bulk hardness (H) is

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$$H = f(t, B, N, D, R, T, t_s, P) \quad (7)$$

Hence, the relationship of π-term can be written as:

$$g(\pi_1, \pi_2, \pi_3, \pi_4)$$

(8)

$$\pi_1 = t^{a1}B^{b1}N^{c1}D^{d1}R^{e1}H \quad (9)$$

$$\pi_2 = t^{a2}B^{b2}N^{c2}D^{d2}R^{e2}t_s \quad (10)$$

$$\pi_3 = t^{a3}B^{b3}N^{c3}D^{d3}R^{e3}P \quad (11)$$

$$\pi_4 = t^{a4}B^{b4}N^{c4}D^{d4}R^{e4}T \quad (12)$$

Dimensionless equation for density (ρ) is

$$\rho = f(t, B, N, D, R, T, t_s, P) \quad (13)$$

Hence, the relationship of π-term can be written as:

$$g(\pi_1, \pi_2, \pi_3, \pi_4) \quad (14)$$

$$\pi_1 = t^{a1}B^{b1}N^{c1}D^{d1}R^{e1}\rho \quad (15)$$

$$\pi_2 = t^{a2}B^{b2}N^{c2}D^{d2}R^{e2}t_s \quad (16)$$

$$\pi_3 = t^{a3}B^{b3}N^{c3}D^{d3}R^{e3}P \quad (17)$$

$$\pi_4 = t^{a4}B^{b4}N^{c4}D^{d4}R^{e4}T \quad (18)$$

Dimensionless equation for tensile strength (σ_y) is

$$\sigma_y = f(t, B, N, D, R, T, t_s, P) \quad (19)$$

Hence, the relationship of π-term can be written as:

$$g(\pi_1, \pi_2, \pi_3, \pi_4) \quad (20)$$

$$\pi_1 = t^{a1}B^{b1}N^{c1}D^{d1}R^{e1}\sigma_y$$

(21)

$$\pi_2 = t^{a2}B^{b2}N^{c2}D^{d2}R^{e2}t_s \quad (22)$$

$$\pi_3 = t^{a3}B^{b3}N^{c3}D^{d3}R^{e3}P \quad (23)$$

$$\pi_4 = t^{a4}B^{b4}N^{c4}D^{d4}R^{e4}T \quad (24)$$

Dimensionless equation for matrix particle size (M) is

$$M = f(t, B, N, D, R, T, t_s, P) \quad (25)$$

Hence, the relationship of π-term can be written as:

$$g(\pi_1, \pi_2, \pi_3, \pi_4) \quad (26)$$

$$\pi_1 = t^{a1}B^{b1}N^{c1}D^{d1}R^{e1}M \quad (27)$$

$$\pi_2 = t^{a2}B^{b2}N^{c2}D^{d2}R^{e2}t_s \quad (28)$$

$$\pi_3 = t^{a3}B^{b3}N^{c3}D^{d3}R^{e3}P \quad (29)$$

$$\pi_4 = t^{a4}B^{b4}N^{c4}D^{d4}R^{e4}T \quad (30)$$

Dimensionless equation for compressive strength (σ_u) is

$$\sigma_u = f(t, B, N, D, R, T, t_s, P) \quad (31)$$

Hence, the relationship of π-term can be written as:

$$g(\pi_1, \pi_2, \pi_3, \pi_4) \quad (32)$$

$$\pi_1 = t^{a1}B^{b1}N^{c1}D^{d1}R^{e1}\sigma_u \quad (33)$$

$$\pi_2 = t^{a2}B^{b2}N^{c2}D^{d2}R^{e2}t_s \quad (34)$$

$$\pi_3 = t^{a3}B^{b3}N^{c3}D^{d3}R^{e3}P \quad (35)$$

$$\pi_4 = t^{a4}B^{b4}N^{c4}D^{d4}R^{e4}T \quad (36)$$

Dimensionless equation for percentage of elongation (e) is

$$e = f(t, B, N, D, R, T, t_s, P) \quad (37)$$

Hence, the relationship of π-term can be written as:

$$g(\pi_1, \pi_2, \pi_3, \pi_4) \quad (38)$$

$$\pi_1 = t^{a1}B^{b1}N^{c1}D^{d1}R^{e1}e \quad (39)$$

$$\pi_2 = t^{a2}B^{b2}N^{c2}D^{d2}R^{e2}t_s \quad (40)$$

$$\pi_3 = t^{a3}B^{b3}N^{c3}D^{d3}R^{e3}P \quad (41)$$

$$\pi_4 = t^{a4}B^{b4}N^{c4}D^{d4}R^{e4}T \quad (42)$$

These equations can be used to predict each responses during mechanical alloying/milling of nanocomposite materials.

Table 1. Details of mechanical alloying/milling input and output parameters and their corresponding symbol, unit and dimensions to be taken for investigation

Classification	Factor	Symbol	Unit	Dimension
Output responses	Crystallite size	d	nm	L
	Bulk hardness	H	MPa	$MT^{-2}L^{-1}$
	Density	ρ	Kg/m^2	ML^{-3}
	Tensile strength	σ_y	MPa	$MT^{-2}L^{-1}$
	Matrix particle size	M	µm	L
	Compressive strength	σ_u	MPa	$MT^{-2}L^{-1}$
	Percentage of elongation	E	-	-
Input parameters	Milling time	t	Min	T
	Ball-to-powder ratio	B	-	-
	Milling speed	N	rpm	T^{-1}
	Ball size	D	µm	L
	Percentage of reinforcement	R	-	-
	Sintering temperature	T	K	θ
	Sintering time	t_s	Min	T
	Consolidation pressure	P	MPa	$MT^{-2}L^{-1}$

B. Modeling using linear and non-linear multiple regression analysis

Regression equation is one of a mathematical relation which relates one independent variable on various responses whereas multiple regression models could relates several independent variables with various responses. Many of real-world applications demand the use of multiple regression models [9, 10].

(i) Multiple linear regression model:

The multiple regression models can be used to forecast the value of each responses Y, given a set of 'n' dependent variables (X_1, X_2, X_3,…,X_n).

$$Y_1 = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots\dots\dots + \beta_n X_{ni} + \varepsilon_i \quad (43)$$

where Y_i is the response and β_0, $\beta_1, \beta_2, \beta_3, \dots, \beta_n$ are regression parameters, $X_0, X_1, X_2, X_3, \dots, X_n$ are covariates and ε_i is the error. It could be written in the matrix form as follows

$$Y_{n+1} = X_{n(r+1)} * \beta_{(r+1)} + \varepsilon_i \quad (44)$$

$$\hat{Y} = X\hat{\beta} \quad (45)$$

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T Y \quad (46)$$

$$\hat{\varepsilon} = Y - \hat{Y} \quad (47)$$

Using the above equations from 43 to 47, multiple linear equation model for each response are to be developed

(ii) Multiple non-linear regression model:

Multiple non-linear regression model is to be constructed using the below equation for each responses

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{u=1}^{k} \beta_{ii} X_i^2 + \sum_{i<j}\sum \beta_{ij} X_i X_j + \varepsilon_i \quad (48)$$

where k indicate the number of factors (i.e. 2), β_0 indicate the free term, β_i indicate the linear effect, β_{ii} indicate the squared effect and β_{ij} indicate the interaction effect.

C. Optimization using Grey relational analysis

Deng (1982) had developed a grey theory which proved to be a successful tool that relates the poor, incomplete and uncertain information. This grey theory can be used to solve the complicated problem which involves multiple responses. In grey theory, the black (0) indicate zero information, the white (1) indicate the fully known information, the value lies between 0 and 1 would indicate the information between black and white [11, 12]. The following step-by-step has to be used in grey system theory.

(i) Data pre-processing

The first step in grey theory is data pre-processing which is required to avoid the suppression of data based on several input and output values. Simply, the data can be converted in the form of comparable one. Several data pre-processing methods are available which can be selected based on the data characteristics in grey theory. Higher the better is one of characteristics which can be used when the target value is infinite and can be normalized and calculated using the below equation:

$$x_i^*(k) = \frac{x_i^o(k) - \min x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \quad (49)$$

Lower the better is another one of characteristics which can be normalized and calculated using the below mentioned equation:

$$x_i^*(k) = \frac{\max x_i^o(k) - x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \quad (50)$$

Further, if the characteristics is exactly on the target, then the data sequence can be normalized and calculated using the below mentioned equation:

$$x_i^*(k) = 1 - \frac{\left|x_i^o(k) - x^o\right|}{\max x_i^o(k) - x^o} \; ; \quad (51)$$

Or, the following formula can also be used to normalize the data which is a basic method.

$$x_i^*(k) = \frac{x_i^o(k)}{x_i^o(1)} \quad (52)$$

where i would start from 1 to m; k would start from 1 to n. The value of m is number of experimental data and the value of n is the number of input parameters. x_i^0 (k) would indicate the sequence in original form, x_i^* (k) would indicate the sequence after data processing, max x_i^0 (k) would indicate the highest value of x_i^0 (k), min x_i^0 (k) would indicate the lowest value of x_i^0 (k) and x^0 would indicate the target value.

(ii) Grey relational coefficient

The characteristics of two systems can be described by grey relational grade in the grey theory and it can be calculated after data-processing. For i^{th} experiment and k^{th} performance characteristics, the value of grey relational coefficient, ξi (k) can be determined as below:

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta\,\Delta_{\max}}{\Delta_{oi}(k) + \zeta\,\Delta_{\max}} \quad (53)$$

where, Δ_{oi} would indicate the difference between the reference sequence and the comparability sequence.

$$\Delta_{0i} = \left\| x_0^*(k) - x_i^*(k) \right\|$$

$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|$$

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|$$

Here, x_0^* (k) indicate the reference sequence and xi* (k) indicate the comparable sequence. ζ indicate the identification coefficient: ζ ε [0, 1]. The lower value of ζ would indicate the larger in distinguished ability.

(iii) Grey relational grade

Once, the grey relational coefficient has been determined, the grey relational grade has to be calculated using mean as below [11]:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad (54)$$

But, the real system would vary which depends on various parameters. Usually, unequal weigh has to be assigned in the real problem and then using Eq. (54) can be used to calculated the grade as:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} w_k \xi_i(k) \qquad \sum_{k=1}^{n} w_k = 1 \quad (55)$$

Here, w_k would indicate the normalized weight on factor k. For the same weight, Eq. 54 and Eq. 55 are become same. The value of γ_i would mention the agreement between the reference and comparable data sequences and then the value become 1. The value of grey relational grade would indicate the influence of response for the particular input parameters.

In order to optimize the responses for the corresponding input parameters, orthogonal array can be used to design and conduct the experiments and then the grey theory can be used to convert multiple response characteristics into single one. The following step by step procedure can be used for this analysis.

1. The importance input parameters and useful responses are to be identified first
2. Then, the number of level in each input parameters are to be determined
3. Based on number of input parameters and its level, the appropriate orthogonal array has to selected and then each process parameters are to be assigned in the table
4. After selecting and assigning the parameters in the table, experiments are to be conducted as per orthogonal array
5. Next, data normalization has to be carried out

6. Calculate the grey relational coefficient and grey relational grade by mean
7. Then, examining the results based on the value of grey relational grade
8. Statistical analysis s also to be used to determine the percentage of contribution of each parameter on each response
9. Now, the optimum process parameters can be find-out and at last, the optimal results are to be validated by conducting the conformation test.

D. Modeling using Artificial Neural Network (ANN)

Neural network based artificial intelligent technique is developed based human brain which is accepted by all the scientist. This technique is based on processing the artificial neurons on the basis of information / data obtained. This method is being applied in real problem as pattern recognition in sensors [13, 14].

Backpropagation neural network (BPNN)

It is being identified that the backpropogation neural network technique is best suitable for various applications (for instance, adaptive control, speech recognition, prediction of stock market etc…) especially for multi response problems [13]. Further, this technique is one which predict the system performance in a faster manner and it has more learning accuracy [13]. There are numerous algorithms available in which Levenberg–Marquardt algorithm (*trainlm*) is best one and it has fastest convergence. Further, this algorithm would give very low value of error when compared to other algorithms and hence, it has been decided to use this Levenberg–Marquardt algorithm (*trainlm*) algorithm in the present research work. The BPNN is a multi-layer network which consisting of input layer, hidden layer(s) and output layer(s) [28]. The basic five steps to be followed in BPNN is given below:

1. First, the data has to be collected based on having some real experimental values.
2. Second, pre-processing of the data.
3. Based on the number of input parameters and output responses, the number of layers has to be designed.
4. Checking the performance of network after simulation.
5. Finally, we have to do the post-processing of our results.

E. Modeling using Fuzzy logic

Next, fuzzy logic can also be used to predict the system behavior based on the experimental results which was developed and invented by Zadeh's [15]. This technique is working based on rules built in the system which is called as fuzzy set [16]. The predicted system behavior would mainly depend on the number of rules or fuzzy set built in the platform. Based on the levels in each input parameters and output responses, the number of membership functions can be used in which more number of membership function would give more accuracy. Therefore, the present research work for developing fuzzy model for predicting the responses during mechanical alloying/milling has been taken.

F. Modeling using adaptive neuro fuzzy inference system (ANFIS) approach

Another one of latest technique in the modeling is adaptive neuro fuzzy inference system which is one of hybrid approach. This approach would give more accuracy when compared to neural network and fuzzy logic as it combined the benefits of both neural network and fuzzy logic [16]. It is a high efficient nonlinear modeling technique which can be used all kind of manufacturing sectors. Based on experimental results, it can be written the fuzzy IF-THEN rules as per ANFIS algorithm which is developed by Takagi and Sugeno; it can be trained which then a well converged artificial expert system would form. The main feature of this ANFIS is it can learn the system in a single step. The Takagi and Sugeno emphasized the following general IF-THEN rule.

$$Rule\, l\, (R^l): IF\ (x_1\ is\ F_1^l,\ and\ \ x_2\ is\ F_2^l\ ....and\ x_p\ is\ F_p^l),$$
$$THEN\ (Y = Y^l = c_0^l + c_1^l x_1 + c_2^l x_2 + ... + c_p^l x_p), \quad (56)$$

Here, the Eq. (56) would indicate the fuzzy set which corresponds to x_i in the l^{th} rule. Y^l would indicate the response to rule number R^l. It is expected that this ANFIS can give well correlated model when compared to other mentioned above methods.

III. EXPERIMENTAL WORK-PILOT STUDY

As a pilot study, Fe-35Mn based bio-degradable alloy was synthesized using high-energy ball milling (Mechanical alloying). The metallic powders of iron (Fe), manganese (Mn), and copper (Cu) with the purity of more than 99% were purchased from Nanografi, Germany. The measured powder particle size of as-received metallic powders are within 45 µm (-325 mesh). The schematic of mechanical alloying process is shown in Fig.2.

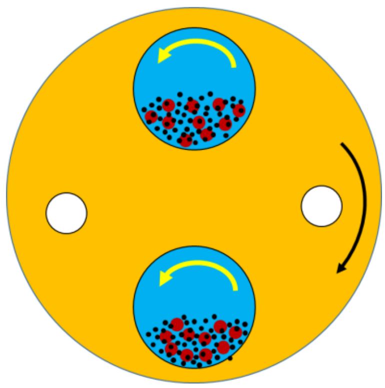

Fig.2. The schematic of mechanical alloying process (two stations high-energy ball mill)

To optimize the performance of Fe-35Mn-5Cu alloy, milling speed (rpm), milling time (h), and ball-to-powder ratio (BPR) were varied during mechanical alloying process. The used parameters are illustrated in Table 2.

Table 2. Various process parameters used as pilot study

Name of parameters	Level 1	Level 2	Level 3
Milling speed, rpm	100	200	300
Milling time, h	1	5	10
BPR	5:1	10:1	15:1

The mechanical alloying was carried out under wet medium for which ethanol was used as medium which will never react with the powders and further, it prevents the formation of oxidization during milling/mechanical alloying process.

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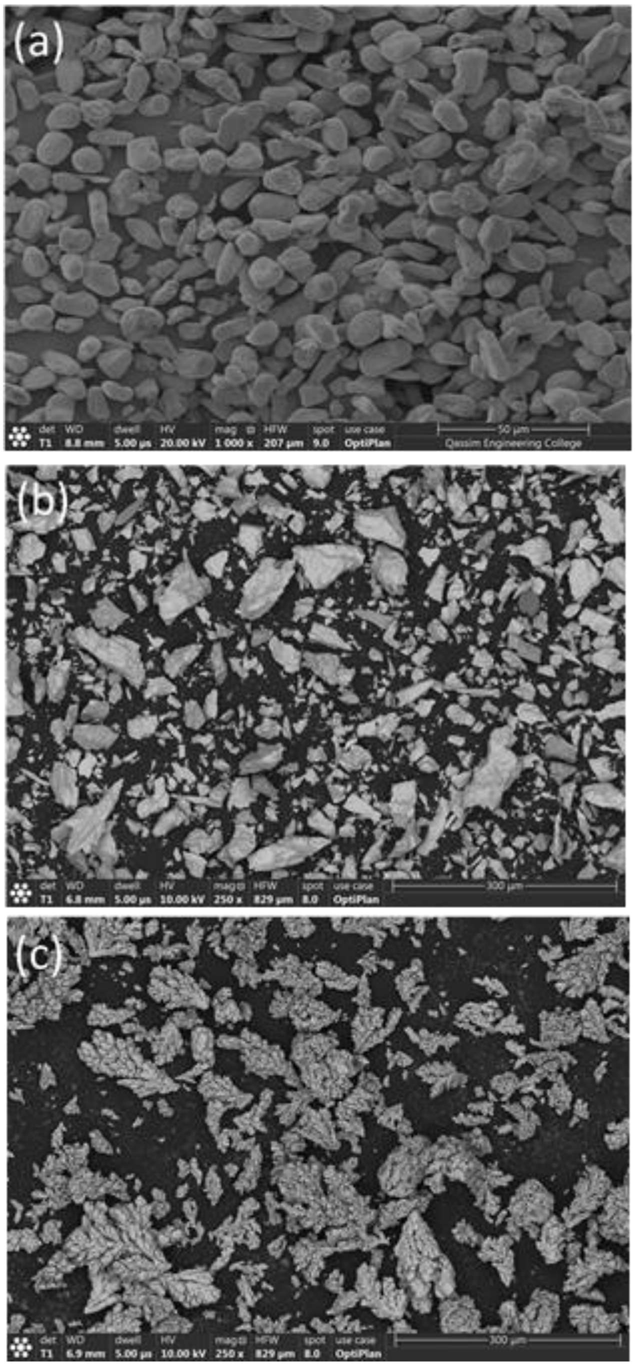

Fig.3. SEM powder surface morphology of as-received iron (Fe), manganese (Mn), coper (Cu) powders

The powder surface morphology of as-received powders and as-milled / mechanically alloyed powders were examined using FEG-SEM. After mechanical alloying process, the hardness of milled powders was measured using Vicker's micro hardness method.

IV. RESULTS AND DISCUSSION

The SEM morphology of as-received Iron (Fe) and Manganese (Mn) powders is shown in Fig.3. From Fig.3, it can be observed that the iron powders possess almost spherical morphology whereas the manganese powders possess polygonal shape. Further, the as-received copper (Cu) powder surface morphology has dendrite like network morphology.

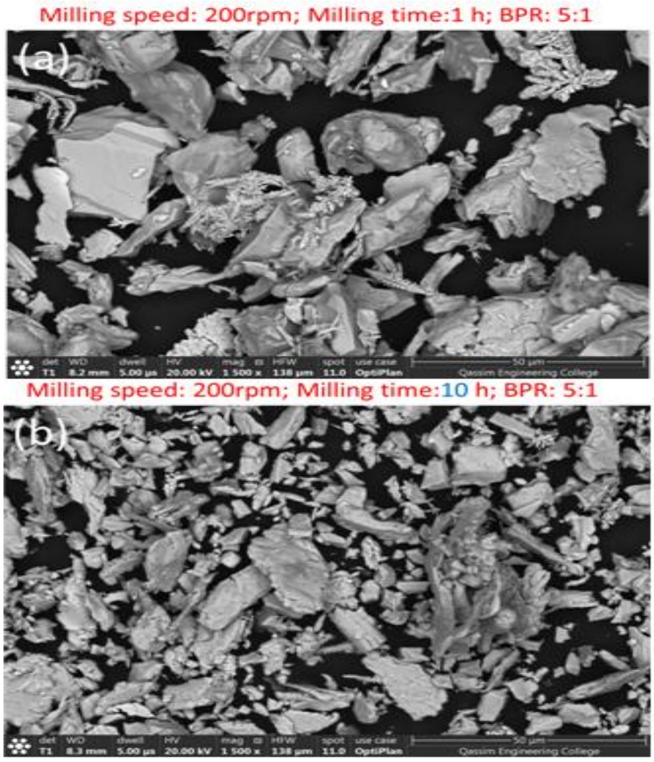

Fig.4. SEM powder surface morphology of mechanically milled powders with different processing parameters: (a) milling speed: 200rpm, milling time: 1h, BPR:5:1; (b) milling speed: 200rpm, milling time: 10h, BPR:5:1

Fig.4 show the SEM powder surface morphology behavior (as an example) of Fe-35Mn-5Cu alloy powders with different milling time. From Fig.4(a), the powder surface morphology results indicate that the powders exhibit very large size at lower milling time (1 h) for the same milling speed and BPR. However, in Fig.4(b), very fine/smaller size of powder particles were observed with flake like shape after 10 h of milling time. These results indicated that the milling time has much influences on the powder surface morphological changes. Obviously, these changes of powder surface morphology will directly reflect the mechanical properties of materials. In general, during mechanical alloying, the charges powders are being crushed, plastically deformed, fractured consequently the shape will be changed after certain milling time. Hence, the shape of powders is changed with different milling time and other processing parameters.

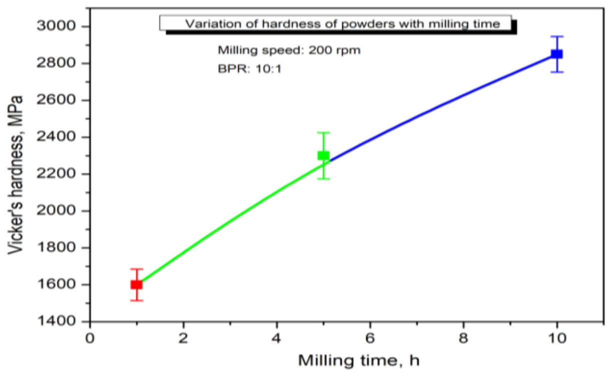

Fig.5. Vicker's hardness strength changes in Fe-35Mn-5Cu alloy powders with different milling time for the same BPR (10:1) and milling speed (200 rpm)

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Fig.5 show the changes of Vicker's hardness of Fe-35Mn-5Cu powder particles with different milling time. The results demonstrated that the observed hardness of mechanically milled powders particles are increased drastically with increasing of milling time. This is attributed to strain hardening occurs in the powder with increasing of milling time. The amount of strain hardening is given by the mechanical milling medium due to ball, powders, and vial collisions. The detailed experimental works, the corresponding modeling works and optimization parts are being analyzed and will be published in separate papers.

V. CONCLUSION

In the present work, the various parameters which affect the performance of mechanical properties of mechanically alloyed powders were analyzed. Based on process parameters, various mathematical modeling techniques including Buckingam π-theory, linear and non-linear approaches, modeling by traditional and non-traditional methods are examined. As a pilot study, experimental work of Fe-35Mn-5Cu alloy powders were manufactured by varying different parameters.

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