# Designing of Intelligent Expert Control System Using Petri Net For Grinding Mill Operation

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**Abstract:-** The paper utilizes Petri_like_net structure in developing an intelligent expert control system to achieve optimum grinding by regulating the parameters of the grinding mill. The work establishes an appropriate theoretical background that helps to predict dynamic breakage characteristics of particle size distribution of materials, adequately supported by experimental data. Feed forward neural network has been employed in the work to adapt the dynamic breakage characteristics of the mill by imparting training using generalized back propagation learning method. The mill has been tuned with the trained parameters and no further training is required so long the desired output is unchanged, irrespective of the input particle size range. In the next phase of the work, using acoustic sensors sound of different mills are recorded and analyzed to identify the operating states of the machines. The rule base adopted from the mill has been designed with the help of the recorded information and implemented using Petri_like_net structure. In real time, the reasoning process generates inference based on the deviation of acoustic signal from the recorded value, which is subsequently converted to control action to achieve optimum grinding. The time of reasoning is compatible with the particle residence time.

**Keywords: Neural network, Sum squared error, Petri_like_net, Acoustic sensors**.

## 1. INTRODUCTION

Conventional control system controls the systems output in some prescribed manner by varying its inputs. Though the control system has been used to analyze and to determine various parameters for stability of a system, but it lacks to acquire information from the environment, i.e. the system does not have the adaptive nature of the input – output behavior. The work aims to develop an instrumentation scheme vis-à-vis an intelligent expert control system [1] to obtain the benefit of closed loop grinding in open loop condition. The purpose of grinding is mainly to reduce the particle size and liberation [2] of pure material. The tumbling mill is a reactor having certain kinetics (rate of breakage) that grinds particles in smaller sizes within a certain residence time [3]. But the process is purely off-line i.e. there is no way to tune the run-time parameters of the mill, if the product deviates from the desired result.

In a tumbling mill the exact state of breakage of particle is quite unpredictable [3] since each particle breaks in different manner. Moreover, it is not possible to install any sensor inside the revolving mill. Therefore, emitted sound of ball mill is used as the radiated parameter for sensing the same of the machine. Two kinds of information, (i) particle size distribution and (ii) variation of acoustic parameters from the desired value provide necessary information to monitor the operation of the mill.

A generalised supervised learning algorithm [4][5] has been employed to establish and verify the breakage characteristics of the particle size distribution where, the weights at two hidden layers of the neural network (NN) mapped as feed and product distribution respectively. The trained weight set of the NN guarantees [6] to generate the desired particle size within a limited size band while further training is to be imparted in case the desired particle size resides outside this range.

The work involves choice of a radiated energy parameter to establish the control schematic. The entire scheme has been adopted from a ball mill and later simulated and verified with a given control model, shown diagrammatically in Fig-1. The sonic probes [7] pick up the sound signature of the circulating mill and compare it to the knowledge base of the mill. While any deviation from the expected sound spectra, the expert controller (EC) fires the appropriate rule to control the speed of dozer motors that brings the system under desired condition. The particle size distribution within a given size range corresponding to a particular sound signature is obtained after a series of laboratory experiments. Nearly fifteen sets of data of different mills under different loading conditions have been recorded that correspond to certain acoustic features. From the recorded value analysing their operational frequency ranges recognizes the machines. Deviation of acoustic signal from its recorded value used as a feedback signal to adjust the run-time parameters of the ball mill for its proper operation.

The rule base of the hybrid expert controller [8] has been constructed from the experimental results of the domain and implemented using a Petri-like-net structure [9][10]. Petri net is widely used in knowledge representation techniques [10] and it has immense scope of application in real time processing due to its inherent parallelism. In the paper the rules are implemented using the place-transition pairs while the 'if-then' part of a rule is mapped at the transition [11] of the Petri net. In this paper the extended- Petri-net (EPN) model has been used to describe the functioning and to analyse the stability of the mill. The stability of the system is guaranteed, which is verified using computer simulation.

The paper has been divided into four sections. In section 2, how a generalised supervised learning algorithm has been used in the work for prediction of particle breakage characteristics has been presented. In section 3, the hybrid expert controller has been implemented using EPN structure. Case study illustrating the model has been discussed in a sub section of section 3. Finally the conclusions are arrived at section 4.

## 2. LEARNING SCHEME

The paper employs a learning scheme for establishing and verification of the predictive grinding in linear zone of particle size distribution and for implementation of the same, a generalised supervised training algorithm, described in our early work [4][5] has been used. In the work a feed forward neural network[12] is employed, instead of considering a single pair corresponding to each input-output node in a training set, multi-valued information in the form of a $p$-dimensional vector ($p$>1) are submitted at each node of the input-output layer of the network. The particle size distribution within different given size band forms the $p$-dimensional input vector at each input node while desired particle size within different specific size band constructs the $p$-dimensional output vector and mapped at each output node of the NN.

The convergence of the algorithm has been successfully tested with experimental and as well as with simulated data, where the convergence has been shown in Fig. 2.

## 3. HYBRID EXPERT CONTROLLER

The second phase of the work is divided into two parts. In the first part, acoustic sensors are used to record the sound of different ball mills under varied load conditions and transformed into frequency domain using first Fourier transform (FFT).

### 3.1 *Extended Petri Net Model*

To simulate the entire scheme of a ball mill, the rule base of the tumbling mill has been designed and realized by an extended-Petri-net (EPN) structure. Before discussing the expert control model a few definitions are given below for the convenience of the reader.

Def. 1**.** An EPN is a directed bipartite graph [10] with ten tuples denoted by

EPN = {P, D, n, T, CT, A, tt, ctt, I, O}

P = $\{p_1,p_2, \ldots\ldots,p_n\}$ is a set of places, represented by "circles",

D = $\{d_1,d_2,\ldots..,d_n\}$ is a set of variables, each $d_i$ is mapped to the corresponding $p_i$, for $1\leq i \leq n$,

n : $P\rightarrow\{0,1\}$, is an association function, represented by a mapping from a place to a binary number.

$n_i$ denotes the truth value of variable $d_i$, in the interval {0,1} and mapped at place $p_i$.

T = $\{t_1,t_2,\ldots.,t_m\}$ is a set of transitions, represent the *'if-then'* part of the rules and denoted by "bars".

CT = $\{ct_1,ct_2,\ldots.,ct_m\}$; is a set of negate transitions, which represent a variable and its complement as its input and output places respectively and denoted by "parallel bars".

$A\subseteq(PxT) \cup (TxP) \cup (PxCT) \cup (CTxP)$ is the flow relations and the elements of A are called 'arcs'.

tt: $T\rightarrow\{0,1\}$, is an association function, represented by a mapping from transition to a binary number where $tt_i$ denotes the firing condition of the rule mapped at transition $t_i$.

ctt: $CT\rightarrow\{0,1\}$, is an association function, represented by a mapping from negate transition to a real number where $ctt_i$ denotes the firing condition of transition $ct_i$.

I and O are two association function which represent the mapping from transitions or negate transitions to their input and output places such that $PxT\subseteq A$, $TxP\subseteq A$ or $PxCT\subseteq A$, $CTxP\subseteq A$, respectively.

Def. 2. Vector N(t) is called the *truth vector,* its *i*-th component represents the truth value of variable $d_i$, mapped at place $p_i$, at time *t*. The number of components of N(t) is equal to the number of places in the EPN.

After formation of the network using rule base of the mill, to start the reasoning process, the network is initialized by assigning truth value to the places. The initialization process is entirely domain dependent. In the reasoning process, tt and ctt are computed synchronously at all transitions and negate transitions respectively following which the truth values at the places are updated which is synchronous too. The whole process together constitutes a forward computation cycle. The process is continued until truth value at all places are stable i.e. same at two successive forward computation cycles. In a point-wise notation the computation of tt, ctt at transitions and negate transitions are described, vide expression (1a) & (1b) respectively.

### 3.2 *Truth Value Updation at Transitions*

The condition for firing a rule is checked first followed by which tt and ctt are computed in the EPN. A transition is called enable provided all its input places possess non-zero truth value. An enabled transition fires generating tt at its output arc. The $tt_j(t+1)$ at transition $t_j$ is computed using expression (1a).

$$tt_j(t+1) = \bigwedge_{i=1}^{m} (n_i(t)) \; ; \quad \ldots \; (1a)$$

where $\bigwedge_{i=1}^{m} n_i(t)$ represents the logical 'AND' of truth value of *m* number of places, i.e. $(p_1,p_2, ..,p_m) \in I(t_j)$.

A negate transition is enabled provided its input place possesses truth value propagated from its predecessor place. An enabled negate transition generates ctt at its output arc, otherwise block further propagation of signal, i.e. the output arc becomes open. The $ctt_j(t+1)$ at transition $ct_j$ is computed using expression (1b).

$$ctt_j(t+1) = \neg\, n_k(t); \text{ if } n_k(t)=n_v(t-1), \text{where } p_k \in \{I(ct_j), O(t_u)\} \text{ and } p_v \in I(t_u)$$
$$= \infty; \text{ otherwise} \quad \ldots \; (1b)$$

### 3.3 *Truth Value Updation at Places*

The computation of truth value at place $p_s$ $(n_s(t+1))$, is carried out using expression (2).

$$n_s(t+1) = \left(\bigvee_{i=1}^{r} tt_i(t+1)\right) \vee \left(\bigvee_{i=1}^{q} ctt_i(t+1)\right); \quad \ldots \; (2)$$

where $p_s \in O(t_1, t_2, \ldots, t_r, ct_1, ct_2, \ldots, ct_q)$ and 'V' represents logical OR operation.

Finally, $N(t+1) = [\, n_1, n_2, \ldots\ldots\ldots, n_z]^T_{(z\times 1)}$, where *z* is the total number of places in the EPN. Thus, current truth value at all places in the entire network is computed from their last value. The minimum value of $t=\tau$, when $N(t+1) = N(t)$ is attained, is called the *equilibrium time* and $N(\tau)$ is termed as *steady-state truth vector*. At steady state, truth value at the concluding places (no output arc) generate inferences, based on which the parameters of the mill has been regulated for achieving the desired product range.

### 3.4 Case Study

To automate the grinding process, the rule base of the machine has been implemented using EPN, described in Fig.3.

The rule base of a tumbling mill is represented in pseudo code:

```
Start:
check(dozer); check(motor_dozer);
co-begin {do in parallel}
if ((dozor) AND (motor_dozer)) are not_o.k.
  then re-initialization(dozer)  AND
(motor_dozer)  else
    begin
      load(dozer);
     get(weight) from load_sensors;
      compute(sum_weight);
  co-end;
     send(sum_weight) to P.E.;
Initialization:
initialize(motor_B.M.); //initialize mill motor
if (B.M._state = idle) then (B.M._status=rectify);
if (B.M._state = jammed) then (B.M._status
=stop);
if (B.M._state =running) then (B.M._status =
o.k);
if (B.M._status = rectify OR stop) then
  begin
    stop (motor_B.M.);
    check (motor_B.M.);
    go to Initialization;
  end;
if (B.M._status = o.k.) then
Ball-mill-working:
co-begin
  get(output);
P.E.= read(output);
get(frequeny-range); // fr=frequency-range
if (fr≥1800) then (B.M._status.= empty);
if (1500<fr<1800) then (B.M._status= unknown);
if (200<fr<300) then (B.M._status.= flotation
cell);
if (B.M._status= empty OR unknown OR
flotation cell) then
begin
   stop (mill);
   check( mill);
    go to Initialization
end;
if (600<fr≤1500) then
   begin
     (B.M._status=running with load varying);
     go to Ball-mill-working;
   end;
  co-end;
end.
```

Fig.3 represents the EPN model of the mill, where 26 places (p), 22 transitions (t) and 4 negate transitions (ct) are used to describe the functioning of the mill. Several check points are defined within the network to test the functioning of the model under various input signals. For different external input signals ( value at place $p_i$ is denoted by $n_i$, for i=1 to 26) such as $n_1$=1, $n_3$=1, $n_{12}$=1 and $n_{24}$=1, the output $n_{26}$ becomes 1, which accurately describe the functioning of the mill, because if dozer is in working state ($n_1$=1, $n_3$=1), if B.M. is initialized properly then while the mill emits sound in between 600 Hz and 1500 Hz, output is generated from the mill.

## 4. CONCLUSIONS

The hybrid system proposed in the paper provides closed loop grinding in open loop condition utilising the effect of particle size distributions. The model is not only valid for ball mill but also expected to work well with other different kind of reactors / crushers / compound machines. Under different training conditions convergence of error in acoustic signature has been investigated and obtained satisfactory results

Acoustic analysis is an integral part of the work. Its importance basically lies with the formation of the knowledge base of the proposed expert controller and generation of feedback signal that is the key factor in close loop information system. This paper demonstrates how Petri net has been used successfully for modeling, monitoring and controlling the activity of a tumbling mill to achieve optimum grinding within residence time.

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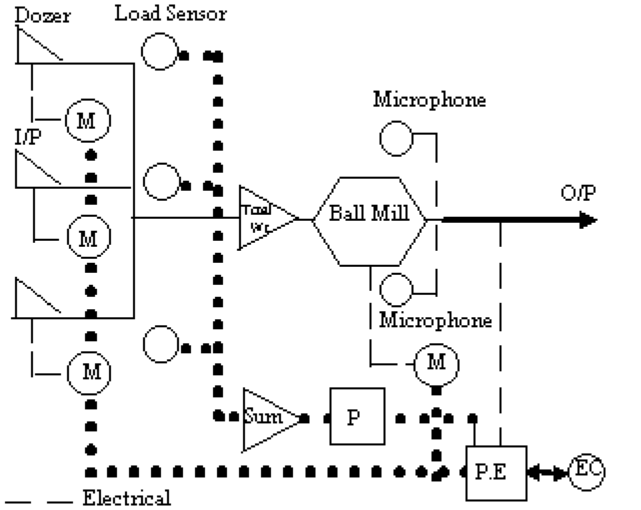


Electrical
Control flow
Internal flow

Fig:1 Schemetic diagram of tumbling mill with expert controller

P: Microcontroller, Digital Signal Processor/Microprocessor
P.E: Processing Element, E.C: Expert Controller, M: Motor

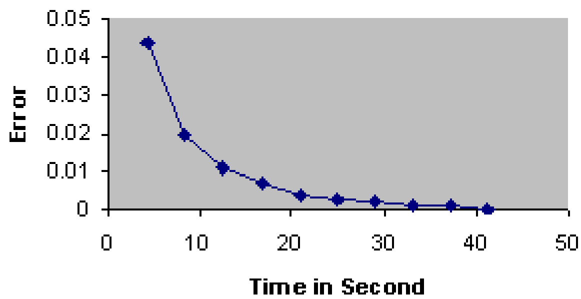


Fig:2 Time vs Error

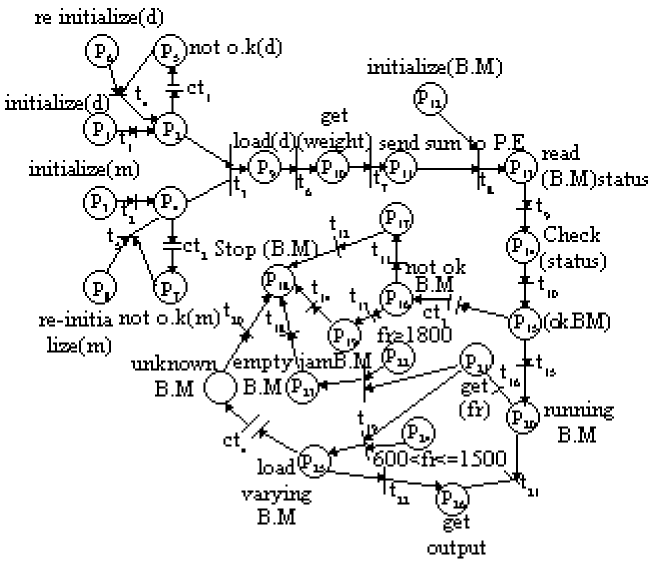


Fig:3 EPN Model of The Ball Mill