MODELLING OF METALLURGICAL PROCESSES USING CHAOS THEORY AND HYBRID COMPUTATIONAL INTELLIGENCE

J. Krishanaiah, C. S. Kumar, M. A. Faruqi, A. K. Roy

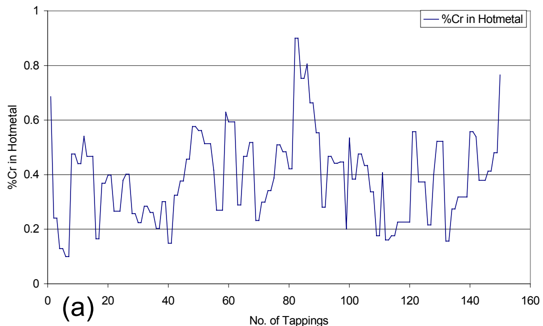
Department of Mechanical Engineering, Indian Institute of Technology, Kharagpur

Abstract: The main objective of the present work is to develop a framework for modelling and controlling of a real world multi-input and multi-output (MIMO) continuously drifting metallurgical process, which is shown to be a complex system. A small change in the properties of the charge composition may lead to entirely different outcome of the process. The newly emerging paradigm of soft-computing or Hybrid Computational Intelligence Systems approach which is based on neural networks, fuzzy sets, genetic algorithms and chaos theory has been applied to tackle this problem In this framework first a feed-forward neuro-model has been developed based on the data collected from a working Submerged Arc Furnace (SAF). Then the process is analysed for the existence of the chaos with the chaos theory (calculating indices like embedding dimension, Lyapunov exponent *etc*). After that an effort is made to evolve a fuzzy logic controller for the dynamical process using combination of genetic algorithms and the neural networks based forward model to predict the system's behaviour or conditions in advance and to further suggest modifications to be made to achieve the desired results.

I. Introduction:

Most of the real-world dynamical systems are difficult to model or control using conventional methods. These include natural ecological systems, immune systems, economies, social systems, metallurgical process like blast furnaces, submerged arc furnaces etc. These kind of systems have further subsystems *e.g.* in the case of furnaces they have many subsystems, which by themselves are known for their non-linearity. The interactions among these subsystems make the total system further more complex. In the case of reactions in the metallurgical process, behaviour of reactions changes considerably, with a small change in charge composition of raw materials, furnace conditions *etc.* The complex systems are spatially and/or temporally extended non-linear systems characterized by collective properties associated with the system as a whole that cannot be simply inferred from the characteristic behaviours of the constituents [1].

One of such systems the Submerged Arc Furnace (SAF) is considered in the present study. The considered SAF produces ferrochrome, which is one of the ferroalloys. To produce ferrochrome, the furnace is required to be charged with combination of ores of chrome and iron, along with the coke and fluxes. The properties of alloy produced are specified in terms of constituents like %Chromium (Cr), %Ferrous (Fe), %Silica (Si) and %Phosphorus (P). Along with these parameters specific power consumption (energy in kilowatts-hours required to produce a ton of hot metal) is also measured. The furnace is tapped on an average every 4 hours that makes nearly 6 taps a day. Figure 1 shows the %Cr in the hot metal and the specific power consumption with time plotted on tapping-to-tapping basis. The nature of the plot is an indicative of a highly time varying system. The SAF is influenced by many systems like thermo-dynamic, electro-chemical, metallurgical, fluid dynamic systems, which are by themselves known for their non-linearities. Combination of these subsystems may lead the system towards a complex behaviour. The modelling of any one of these subsystems is not representative of the total behaviour of the SAF. It is observed that the SAF is very much dependent on the immediate past. This property drives the system into non-linear direction, *i.e.* the relationship among the system parameters at one point of time is not true in the course of time. This implies that the relationships evolve over time.



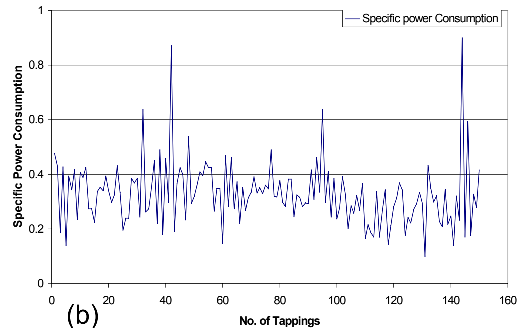


Figure 1: (a). Variation of %Cr in Hot metal produced (b) Specific power consumption variation of the considered SAF (Shown in normalized scale)

To tackle this kind of real-world systems a new set of paradigms like fuzzy sets, chaos theory with combination of genetic algorithms and artificial neural networks have recently emerged. For example, by analysing chaotic signals observed from a complex system and by using fuzzy and neuro-fuzzy techniques, one can interpret and identify the underlying deterministic laws, whose mathematical model is not easy to obtain [2]. These approaches make it possible to predict, control and identify complex phenomena that were once regarded as noise in past. One way of modelling and controlling a non-linear drifting process is to develop an inverse neuro-model of process plant (basically controller is an inverse of the plant itself) using the standard backpropagation algorithms and then to retrain it in real-time allowing the error to propagate through the plant and thus make it learn the current relationships [3]. This approach has been successful in spite of many-to-one relationship between the desirable outputs and required inputs. To avoid this problem of one-to-many solutions, it has been suggested in [4, 5] that a feed-forward neuro-model may be developed first and then a fuzzy logic controller for this may be developed using the genetic search technique. This provides the required inverse relationships. This method appears to be one of the better methods to develop a controller for the plant. However both these are brute force approaches and in practice may require considerable energy and effort to make the plant produce desirable results.

The analysis of the dynamical systems using chaos theory is gradually becoming popular in areas like forecasting the financial system, analysis of the EEG data for understanding the condition of the patients [6], analysing financial organisations [7] *etc.* In this work a time-series data is collected from an Industrial SAF, which is considered to be a non-linear system. This particular data has been used throughout this paper for all the work-done. It has been further shown by Weeks and Burgess [8] that if a proper model of a chaotic system is available it can be driven towards a desirable goal using its sensitivities to various inputs.

This work is in the direction of developing a fuzzy controller based on forward neuro-model with the optimisation capability of genetic algorithms. The forward neuro-model is one-step future predictor and so is the fuzzy logic controller. The paper is organised in five sections including introduction as section I. Section II discusses the development of neuro-model of the SAF and its optimum training conditions for better prediction of immediate future outputs. In section III, the behaviour of the process will be analysed and discussed in the context of chaos theory and the necessary conditions required for the presence of chaos signature in the process. Next section IV discusses the Hybrid Computational Intelligent Systems' (HCIS) approach model. Conclusions are drawn in section V.

Artificial Neural Networks are well known for their approximation, smooth interpolation capabilities and mapping input-output relations of the systems' parameters. The considered SAF's forward model is developed based on the operational data collected from an Industrial SAF. The next section deals with the development of the feed-forward neuro-model of the SAF.

II. Development of Neuro-Model:

As mention earlier, the process is more dependent on the near past. Thus the developed model is used only to predict one-step ahead. In this framework first a feed-forward neural networks model of the industrial SAF has been developed for predicting the behaviour in advance using real plant data. The behaviour here implies specific power consumption and other parameters like composition of the hot metal produced *etc*, which are crucial parameters and give the idea of the furnace state. The hot metal composition is taken as output of the neuro-model along with the specific power-consumption. The inputs to the neuro-model are the charge composition (weight of different ores 12 in number, cokes 5 in number and fluxes 5 in number) and load maintained (input power) at the furnace. This decides a total 23 inputs and 5 outputs (4 hot metal compositions and one specific power consumption) of the neuro-model. To train the model standard backpropagation algorithm has been used. The feed-forward neuro-model learns the process dynamics very well with the patterns presented to it, and it gives a low mean square error (MSE) during the training as well as testing. When this neuro-model is tested over a time span that follows the training time span, the predicted values continue to diverge and MSE increases rapidly. This diverging phenomenon in the prediction is hypothesized to be due to the presence of the chaos in the process. This hypothesis is proved with the help of the chaos theory by calculating the Lyapunov exponent and embedding dimension *etc.*

One of the other important characteristics of the chaotic systems is that they are sensitive to the initial conditions. The chaotic nature of the process makes the furnace operating conditions drift in some direction or other. It is difficult to estimate the direction of the drift using the conventional tools. In this framework the SAF process condition is analyzed using chaos theory. Next section discusses briefly about the application of chaos theory.

III. Existence of Chaos in the Process:

Deterministic chaos as a fundamental concept has been established very well in the literature in the last decade. The deterministic chaos and chaos are interchangeably used in literature. Takens' embedding theorem states that any non-linear process with chaos in it can be modelled to whatever accuracy by choosing correct embedding dimension. The process of embedding a single time series is as follows:

The scalar series is converted to a series of vectors *x(.)* of variable *x,* and then

$$X(t) = f\{x(t), x(d+t), x(2d+t), \ldots\ldots, x(md+t)\}$$

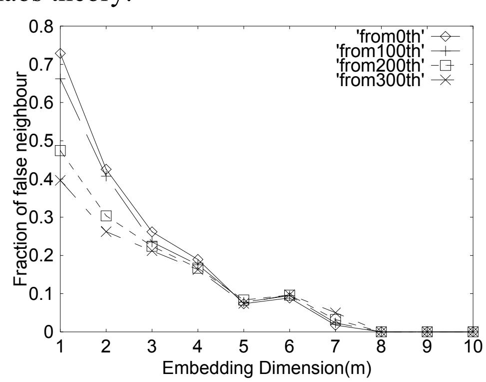


Figure 2: Calculated embedding dimension of the plant

Where d is the separation or also called delay parameter, and m is the embedding dimension and t time.

Embedding dimension gives the idea of dimensionality of the process. Figure 2 shows the calculated embedding dimension based on one of the measurable parameters of the considered plant starting at different instances. In each case the dimensionality of the process is same. To calculate the embedding dimension and other parameters for analysing the chaos in a given time-series data many public domain software tools are available. One of them is TISEAN (Time Series Analysis) package [9] with online documentation. This package can calculate several parameters like embedding dimension, maximum Lyapunov exponent, delay coordinates *etc.* and can be used to analyse for the existence of the chaos in the process.

The value of Lyapunov exponent (λ) gives the idea of the process condition. If λ is positive then the chaos exists in the process. In the present case the λ is found to be positive for all the instances. They are some more indices through which the process condition can be identified. The sum of all the positive Lyapunov exponents from the spectrum of exponents gives the Kolmogorov-Sinai (KS) Entropy and the Kaplan-Yorke Dimension, which is the dimension of strange attractor can be calculated from the non-spurious Lyapunov exponents. These are listed below Table 1 for both day average data and 4-hour average data of the furnace.

TABLE 1:Calculated indices of the plant (SAF)

Data	Max. Lyapunov Exponent	KS-entropy	KY-Dimension
Day Avg. data	0.763	0.0579	10.0
4hour Avg. data	0.2159	0.784	8.3

IV. Development of Model in HCIS approach:

The Hybrid Computational Intelligent Systems (HCIS) approach has recently found its way into the process control. In this approach as mentioned earlier first a feed-forward neuro-model is developed. Based on the developed neuro-model a fuzzy logic controller that is an inverse model of the plant is evolved with the searching and optimisation capabilities of the genetic algorithms. Figure 3, shows the framework for evolving the fuzzy logic controller.

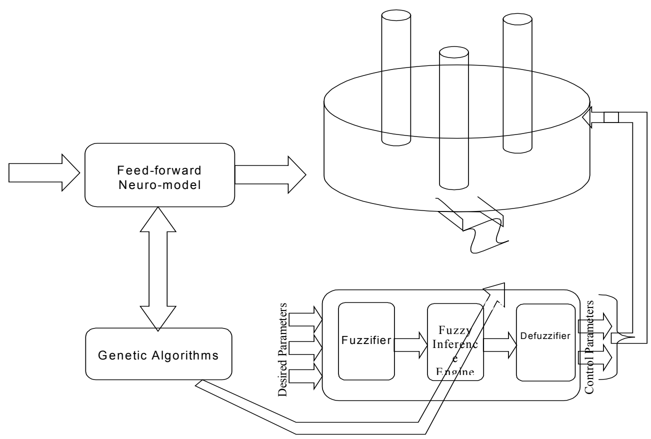


Figure 3: Framework of Hybrid Computational Intelligent Systems approach

The fuzzy logic controller (FLC) has four inputs and six outputs. Here four inputs are desired outputs from the furnace, and six outputs from the FLC are the inputs to the furnace to be charged and maintained. The membership functions are chosen as *low, medium and high* and are trapezoidal in shape. With four inputs, six outputs and three membership functions, theoretically speaking the number of maximum possible rules are 81 ({number of membership functions} $^{\text{(number of inputs)}}$). For a given desired output from the furnace, FLC suggests the inputs to be charged to the furnace.

Conventionally the fuzzy rule-base is built from the knowledge of experienced operators. In this framework the antecedent part of the rule-base is fixed, and the consequent part of the rule-base is evolved using combined effort of the genetic algorithms searching capability [10] and neural networks' interpolating capacity. Each individual string in the genetic pool represents a controller's consequents part of the rule-base and the shape of the membership functions. The

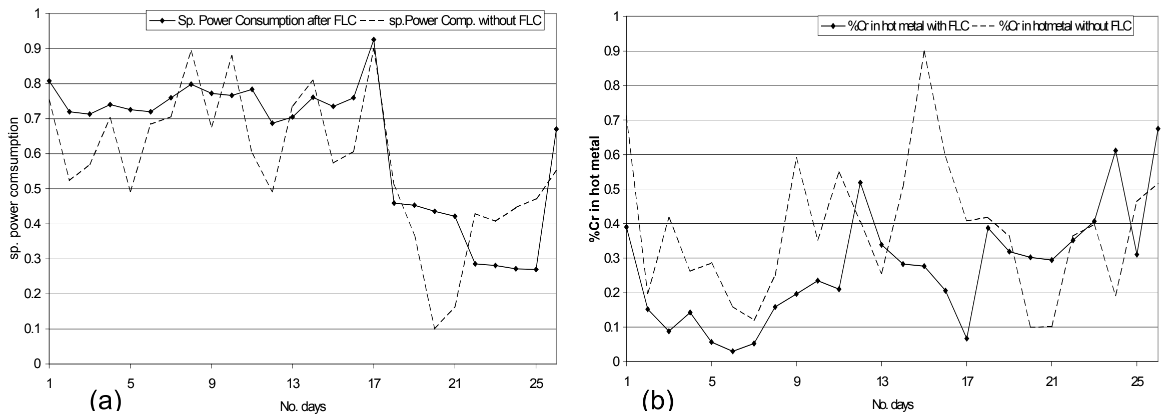


Figure 4: Comparison of results with FLC (Solid lines) and without FLC (doted lines) (a) Specific power consumption, (b) %Cr in hot metal

total population of the pool is taken to be 100 in number. The fitness function for the GA is the feed-forward neuro-model. The fittest controller produces least prediction error for that immediate future. The final evolved fittest individual is encoded into the rule-base and membership functions. The Inference Engine of the FLC is updated with these rule-base and membership functions.

Figure 4 (a and b) show the furnace model output controlled by FLC evolved through above-mentioned approach. Figure (a) represents the specific power consumption, and (b) represents the %Cr in hot metal with (solid line) and without (dotted line) FLC. From these plots it can be seen that the variation in the furnace behaviour is much less when compared to furnace behaviour without FLC.

V. Conclusions:

This model can be further improved by choosing more membership functions for FLC (for example five instead of three), which may give improved control over the furnace. The optimisation process using GA can be improved by implementing a faster way of converging. The developed framework is under implementation on an Industrial SAF.

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VI. References:

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