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MOISTURE CONTENT PREDICTION OF WOOD DRYING PROCESS USING SVM-BASED MODEL

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Abstract. *In this paper, a moisture content predictive method is proposed for wood drying process by using nonlinear model based on support vector machine. In detail, the properties of the moisture content are analyzed during wood drying, which shows that the moisture content is mainly determined by drying temperature and equilibrium moisture content and that water in wood consists of two forms: free water and bound water. For ensuring high predictive accuracy, a moisture content predictive model related to drying temperature and equilibrium moisture content is built by using support vector machine technique. Further, practical parameters selection of SVM modelling is investigated. Also, to filter large noise of training data, infinite impulse response filter technique is considered. By using the built model, moisture content of wood drying process is predicted, including free moisture content and bound moisture content. Finally, simulation results are given to show the effectiveness of the proposed method.*
Keywords: Moisture content, Nonlinear modelling, Support vector machine, Parameter selection

1. **Introduction.** In general, in order to reduce wood deformation and cracking after using, wood needs to be dried. Wood drying is a process of removing water, that is, the decreasing process of moisture content (MC). The quality of wood drying is affected directly by the change of MC. For wood drying, there exist two drying methods, namely, natural drying and artificial drying [1]. The change of MC is uncontrolled for natural drying. By using artificial drying method, wood can be dried to any desired low MC, and drying process can be controlled such that drying quality of wood can be adjusted such as cracking and deformation. However, cost energy is its drawback. In order to improve drying quality and decrease energy consumption and drying time, many drying techniques have been considered by researchers for wood drying [1-6]. These researches show that moisture content prediction is an important aspect to design an effective drying scheme. As a result, a moisture content predictive approach is considered in this paper.

It is well known that people make an attempt to set up model and use it to improve predictive accuracy such that model based predict technique is investigated for moisture content prediction. For MC modelling of wood drying, a number of methods were presented [2-5]. In 1984, diffusion model of MC is proposed by Siau [2]. However, it is based on gradient of chemical potential, not a direct relationship between MC and determinant. The change of MC depends upon a number of factors, the most important of which are the temperature (T) and equilibrium moisture content (EMC). That is, MC of wood is determined by temperature and EMC during wood drying. Simpson and Tschernitz developed a simple MC model related to the two variables [3]. However, it is an approximate model and mainly used to estimate drying time. In fact, it is a complex nonlinear relationship among temperature, EMC and MC, and not easy to describe accurately by theory model. However, it is easy to measure temperature, EMC and MC by using corresponding sensors. Therefore, a nonlinear moisture content predictive model related to drying temperature and equilibrium moisture content is considered by using modelling method based on statistical learning theory. Moreover, by analyzing properties of moisture content, water in wood can be presented as free water and bound water and quality of wood drying is mainly determined by the change of bound moisture content. Therefore, we need further analyze the change condition of free moisture content and bound moisture content. That is, free moisture content model and bound moisture content model are also considered to estimate the removing situations of free water and bound water.

For modelling based on statistical learning theory, there exist three main kinds of methods: least square (LS) method, neural network (NN) method and support vector machine (SVM) method. Least square modelling method is a linear regression method to model the relationship between one dependent variable and one or more independent variables, such that the model depends linearly on the unknown parameters to be estimated from the data [7]. That is, least square method is mainly used to fit a generalized linear model. Neural network method can be used as an arbitrary function approximation mechanism by learning from observed data [8]. However, it often leads local minima or overfitting caused by empirical risk minimization principle. Support vector machine method, which is based on the principle of structural risk minimization, has been proposed to modelling by solving global optimization problems of model output [9-13,15]. As a result, in this paper, moisture content modelling method is proposed by using SVM technique, where temperature and EMC are model input; MC is model output. However, the quality of SVM model depends on a proper setting of SVM parameters, and the main issue for practitioners trying to apply SVM modelling is how to set these parameters for a given data set. Although there exist on appropriate setting of SVM parameters on SVM regression, there is clearly no consensus and contradictory opinions [12,13,15]. Thus, practical selection of SVM parameters is also investigated. Moreover, there may be obvious estimating error when there is large noise in training data. For this issue, infinite impulse response (IIR) filter technology is investigated to filter the large noise of the training data [14].

In this paper, the remained contents are shown as follows. In Section 2, the property of the moisture content is analyzed during wood drying. After that, a modelling method of moisture content is presented by using support vector machine technique, where practical parameters selection is investigated. Also, infinite impulse response filter technique is considered in Section 3. Then, moisture content is predicted by using the proposed model. Following this, simulation results are given to show the effectiveness of the proposed method. Finally, Section 5 draws the conclusion of this paper.

2. **Properties Analysis of Moisture Content.**

Moisture content is the quantity of water contained in the wood. It is defined by Siau in 1984 shown as the following formula [2].

$$MC = \frac{M_g - M_d}{M_d} \tag{1}$$

where M_g is green wood weight and M_d drying wood weight.

Equilibrium moisture content is the moisture content at which wood is neither gaining nor losing moisture. It is a dynamic equilibrium and determined by relative humidity and dry-bulb temperature. Under known relative humidity and temperature, EMC can be calculated according to Keylwerth diagram shown in Figure 1 [6]. In the figure, horizontal axis denotes relative humidity and vertical axis is dry-bulb temperature, and another two group lines denote EMC and wet-bulb temperature, respectively. Relative humidity can be calculated by dry-bulb temperature and wet-bulb temperature. Then, dry-bulb temperature and relative humidity determine EMC together.

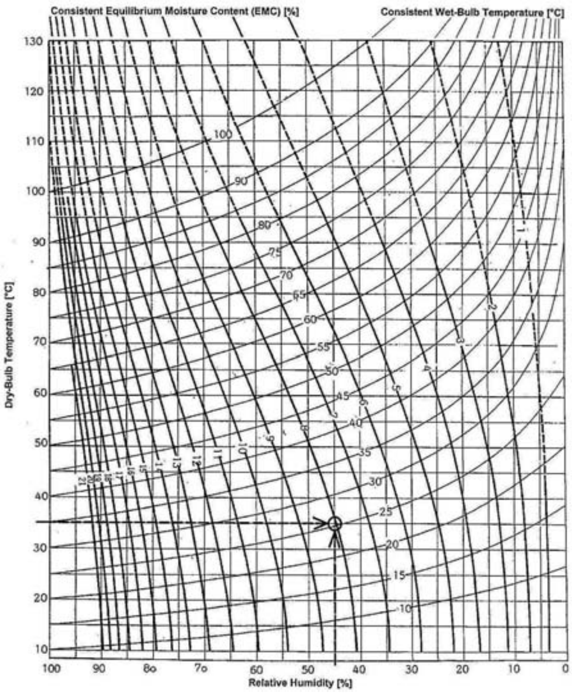

Figure 1. Keylwerth diagram [6]

From Figure 1, we can see that change of moisture content mainly depends upon temperature and equilibrium moisture content. That is, temperature and EMC are regarded as control variables to obtain effective change condition of MC. In general, it is a very complex nonlinear relationship among them, and is not easy to describe accurately by using theory model. However, temperature, EMC and MC can be measured by using temperature, EMC and MC sensors, respectively. Therefore, in this paper, a nonlinear moisture content predictive model related to drying temperature and equilibrium moisture content is considered by using modelling method based on statistical learning theory.

Furthermore, water in wood can be presented as two forms: free water and bound water. Free water is the bulk of water contained in the cell lumina, which is only held by capillary forces. But, bound water is bound to the wood via hydrogen bonds. So, when green wood dries, it is first to remove free water from green wood. The moisture content at which free water is completely removed is defined as the fiber saturation point (FSP) which is 20% to 30% for most woods. Then, moisture content can be described by bound moisture content MC_b and free moisture content MC_f as the following form [2].

$$MC = MC_b + MC_f \tag{2}$$

$$MC_b = 2\frac{MC_b^* - MC_{fsp}}{1 + exp\left\{\frac{2(MC - MC_b^*)}{MC_{fsp} - MC_b^*}\right\}} + MC_{fsp} \tag{3}$$

$$MC_f = -2\frac{MC_f^* - MC_{fsp}}{1 + exp\left\{\frac{-2(MC - MC_f^*)}{MC_{fsp} - MC_f^*}\right\}} + 2(MC_f^* - MC_{fsp}) \tag{4}$$

where MC_{fsp} is moisture content at FSP. MC_b^* is smaller than MC_{fsp} and MC_f^* larger, where MC_b^* and MC_{fsp} equal to minimum MC and $(MC_f^* + MC_b^*)/2$, respectively. During removing free water, most physical properties are unaffected, such as strength and shrinkage. However, when the wood is dried below the FSP, these properties of woods have a considerable change. It also leads that change rate of moisture content of wood is largest at FSP. As a result, moisture content is considered as MC_{fsp} at the point which has maximum change rate of moisture content between 20% and 30%.

From the above analysis, it is clear that the quality of wood drying is mainly determined by the change of bound moisture content. Therefore, we need further analysis the change condition of free moisture content and bound moisture content to improve drying quality. Then, free moisture content model and bound moisture content model are also considered to estimate the removing situations of free water and bound water. According to (3) and (4), free moisture content and bound moisture content can be calculated. As a result, free moisture content model and bound moisture content model can also be set up by using modelling method based on statistical learning theory, respectively.

3. **Moisture Content Prediction Based on SVM Model.** In this paper, SVM is considered to build MC model and MC is predicted by using the built MC model.

3.1. **SVM modelling technique.** A version of SVM for regression was proposed in 1996 by Vapnik et al. The model produced by support vector regression (SVR) depends only on a subset of the training data, because the cost function for building the model ignores any training data close to the model prediction (within a threshold ϵ) [12]. Support vector regression is concerned with estimating a real-valued function shown as follows.

$$f(\tilde{x}) = w \cdot \tilde{x} + b,\ w \in R^d,\ b \in R \tag{5}$$

which is based on a finite number set of independent and distributed data $(\tilde{x}_i, \tilde{y}_i)$. $\tilde{x}_i$ and $\tilde{y}_i$ denote input and output respectively, w is weight vector and b is offset. In Vapnik's ϵ-insensitive support vector regression, the aim is to find a function $f(\tilde{x}_i)$ which allows error of $\tilde{y}_i$ is no more than ϵ, and makes $\tilde{y}_i$ flat for all the training data. Considering more interferential error, non-negative slack variables ξ and ξ^* are introduced. Then, the optimization problem can be described as the following form

$$\min_{w,b} \frac{1}{2} w^T \cdot w + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \tag{6}$$

$$s.t. \begin{cases} \tilde{y}_i - (w^T \cdot \tilde{x}_i + b) \le \epsilon + \xi_i \\ (w^T \cdot \tilde{x}_i + b) - \tilde{y}_i \le \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, i = 1, \dots, n \end{cases}$$

where C is a positive constant and to control the punishment to the samples beyond the error-accuracy parameter ϵ, which is denoted as penalizing parameter. Generalization to kernel-based regression estimation by introducing Lagrange multipliers (α, α^*), we can arrive at the following optimization problem.

$$\max_{\alpha,\alpha^*} W(\alpha, \alpha^*) = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} Q_{ij}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) + \sum_{i=1}^{n} \tilde{y}_i(\alpha_i - \alpha_i^*) - \sum_{i=1}^{n} \epsilon(\alpha_i + \alpha_i^*) \tag{7}$$

$$s.t. \begin{cases} \alpha_i, \alpha_i^* \in [0, C], i = 1, \dots, n \\ \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \\ K(\tilde{x_i}, \tilde{x_j}) = \langle \tilde{x_i}, \tilde{x_j} \rangle = Q_{ij} \end{cases}$$

Ultimately the regression estimate takes the form

$$\begin{aligned} f(\tilde{x}) &= \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\langle \tilde{x_i}, \tilde{x_j} \rangle + b \\ &= \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(\tilde{x_i}, \tilde{x_j}) + b \end{aligned} \tag{8}$$

where $K(\tilde{x_i}, \tilde{x_j}) = \langle \tilde{x_i}, \tilde{x_j} \rangle$ is kernel function that gives two vectors in input space and returns the dot product in feature space. That is, linear regression in a high dimensional space corresponding to nonlinear regression in the low dimensional input space can be realized by mapping the input vectors into a feature space. That is, nonlinear regression problem is resolved by linear regression form.

There are many kernel functions used in SVM, such as polynomial function, Gaussian function and hyperbolic tangent [9-11]. The Gaussian function shown in Equation (9) is used extensively in numerous applications in engineering, physics, and many other fields, where real-valued random variables often tend to cluster around a single mean value.

$$K(\tilde{x_i}, \tilde{x_j}) = exp\left(-\frac{||\tilde{x_i} - \tilde{x_j}||^2}{2\sigma^2}\right) \tag{9}$$

where parameter σ is the variance which is the measure of the width of the distribution, namely, σ is called as kernel width parameter.

For the wood drying process, training input vector consists of temperature and equilibrium moisture content, output vector is moisture content. By training, weight vector w and offset b in (5) are obtained, that is, moisture content model can be derived. However, the quality of MC model based on SVM depends on a proper setting of SVM parameters, and the main issue for practitioners trying to apply SVM modelling is how to set these parameters for a given data set. Under the above case, parameters of support vector algorithm include weight vector w, offset b, slack variables ξ_i, ξ_i^* and Lagrange multipliers α_i, α_i^*, penalizing constant C, error-accuracy parameter ϵ and kernel width parameter σ. Some parameters can be automatically determined, such as weight vector w, offset b, slack variables ξ_i, ξ_i^* and Lagrange multipliers α_i, α_i^*. Such that, SVM estimation accuracy depends on C, ϵ and σ. As a result, practical selection of the three SVM parameters is investigated in the following subsection.

3.2. **Practical parameter selection of SVM.** In the above SVM, C is penalizing parameter, which determines the trade off between the model complexity (flatness). ϵ is error-accuracy parameter, and it controls the width of the ϵ-insensitive zone for fitting the training data. σ is kernel width parameter, which is appropriately selected to reflect the input range of the training data.

Although there exist on appropriate setting of SVM parameters on SVM regression [13], there is clearly no consensus and contradictory opinions. So, practical selection method of the three SVM parameters is presented according to our empirical evidence shown as follows.

(1) Kernel width parameter σ. It is the measure of the width of the distribution, namely, noise variance. In practice, the noise variance can be calculated by the squared sum of residuals of the training data, which is expressed as following form.

$$\begin{aligned} \sigma^2 &= E(\tilde{x_i})^2 \\ &= \frac{1}{n}\sum_{i=1}^{n}(\tilde{x_i})^2 \end{aligned} \tag{10}$$

where n is the training data number.

(2) Penalizing parameter C. Practical selection of parameter C is determined directly by the training data. In this paper, selecting parameter C equals to the range of output values.

(3) Error-accuracy parameter ϵ. In general, the value of ϵ should be proportional to kernel width parameter σ which can be regarded as known value according to the above description [13]. However, the value of ϵ should also be related to the number of training data. As a result, according to our experience, the error-accuracy parameter ϵ is selected as follows.

$$\epsilon = \frac{2\sigma}{\sqrt{n}} \tag{11}$$

3.3. **IIR filter for training data.** Further, when there is large noise in the given training data, there may be obvious estimating error. Especially, the measurement data may be mistake under sensors fault. For this issue, we hope that large noise is filtered. That is, a filter technique is considered for the given training data. In this paper, infinite impulse response (IIR) filter technique is investigated. IIR filters may be implemented as either analog or digital filters. Here, digital IIR filter is used, where the output feedback can be immediately apparent in the equations defining the output. However, in designing IIR filters it is necessary to carefully consider the "time zero" case in which the outputs of the filter have not yet been clearly defined. The mathematical description is shown as follows.

$$\sum_{j=0}^{j=V} a_j z_o[m-j] = \sum_{i=0}^{i=P} b_i z_i[m-i] \tag{12}$$

where P is the feedforward filter order, b_i the feedforward filter coefficients, V the feedback filter order, a_j the feedback filter coefficients, $z_i[m]$ the input signal and $z_o[m]$ the output signal [14]. To facilitate the use, the form, on which the output signal is related to the input signal, can be obtained.

$$\begin{aligned} z_o[m] =& \frac{1}{a_0}(b_0 z_i[m] + b_1 z_i[m-1] + \cdots + b_P z_i[m-P] \\ &- a_1 z_o[m-1] + a_2 z_o[m-2] + \cdots + a_V z_o[m-V] \end{aligned} \tag{13}$$

4. **Simulation Results.** In this paper, Sugi wood drying is considered by using drying kiln made by SECEA shown in Figure 2, where the middle temperature (about 80-100) drying technique is adopted by using steam heating.

In the above wood drying system, besides drying kiln, there are still heating equipments, measuring instruments, draught fans and controller. Heating equipments provide heating

FIGURE 2. SECEA drying kiln

steam. Measuring instruments include temperature sensors, moisture content sensors and equilibrium moisture content sensors. Draught fans are used to control the moisture content in the environment. Controller is designed to improve drying quality and decrease energy consumption and drying time. In this system, two temperature sensors, two EMC sensors and six MC sensors are mounted in the SECEA drying kiln such that training sample data include two temperature units, two EMC units and six MC units. To set up moisture content model by using SVM technique, two temperature units and two EMC units are the input vector, that is, the dimension of input vector is 4, and the output is MC which is the mean value of six MC units. That is,

$$(x_n, y_n) = \left(\begin{bmatrix} T_n^1 \\ T_n^2 \\ EMC_n^1 \\ EMC_n^2 \end{bmatrix}, MC_n \right), \quad n = 1, \ldots, 1030 \tag{14}$$

By training, the moisture content predictive model is obtained, where penalizing constant is $C = 37.1833$, error-accuracy parameter $\epsilon = 0.3771$ and kernel width parameter $\sigma = 6.0515$. Then, a group of input data is given to predict output of MC model. The predictive result by using SVM-based moisture content model is shown in Figure 3 and Figure 4 is the three-dimensional relationship among temperature, EMC and MC.

However, from Figure 3, it is also clear that there exist obvious predictive error sometime on the first, third and sixth days for SVM-based model. That is because the measurement data may be mistake during this period. To resolve this issue, IIR filter is designed as follows.

$$z_o[m] = K * z_o[m-1] + (1-K) * z_i[m] \tag{15}$$

where filter coefficient $K = 0.8$. The predictive result with IIR filter by using SVM-based moisture content model is shown in Figure 5. It is clear that predictive error has been decreased during the measurement data is mistake.

Moreover, free moisture content model and bound moisture content model are also set up by using SVM technique. According to the training data, MC_b^* and MC_{fsp} equal to

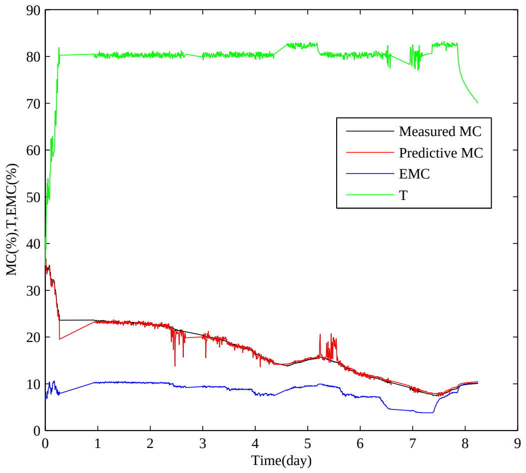

FIGURE 3. SVM-based MC predictive result

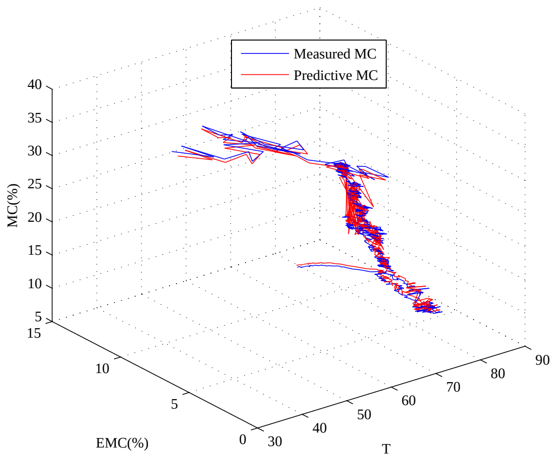

FIGURE 4. SVM-based T-EMC-MC relationship

7.8% and 24.7%, respectively. The training sample is constructed as follows.

$$(x_{fn}, y_{fn}) = \left(\begin{bmatrix} T_n^1 \\ T_n^2 \\ EMC_n^1 \\ EMC_n^2 \end{bmatrix}, MC_{fn} \right), \quad n = 1, \ldots, 1030 \tag{16}$$

$$(x_{bn}, y_{bn}) = \left(\begin{bmatrix} T_n^1 \\ T_n^2 \\ EMC_n^1 \\ EMC_n^2 \end{bmatrix}, MC_{bn} \right), \quad n = 1, \ldots, 1030 \tag{17}$$

where MC_{fn} and MC_{bn} are free moisture content and bound moisture content, which can be calculated by (3) and (4). The predictive results of free moisture content and bound moisture content are shown in Figures 6 and 7, respectively. Figure 6 shows the free moisture content is reduced quickly above fiber saturation point, but the change of the bound moisture content is shown in Figure 7. Figure 8 is the change condition of free

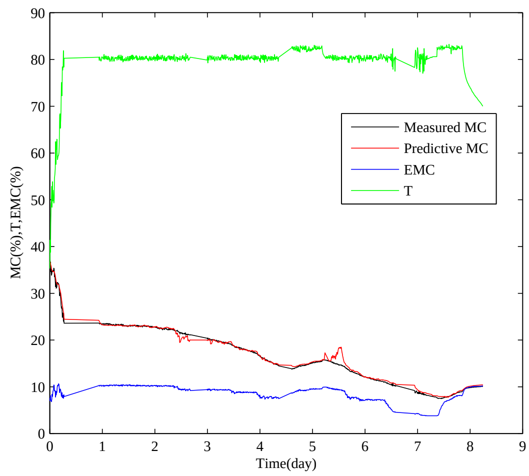

FIGURE 5. MC predictive result with IIR filter

moisture content together with bound moisture content. From these figures, it is easy to see that fiber saturation point is at 24.7% moisture content, and it is difficult to remove water below fiber saturation point.

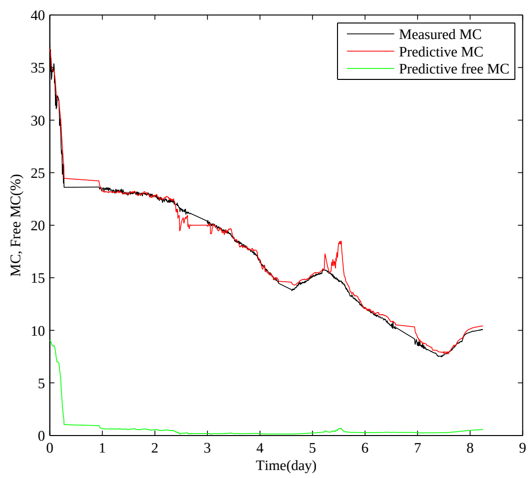

FIGURE 6. Free MC predictive result

5. **Conclusions.** In this paper, by using training data produced by SECEA drying kiln, a moisture content predictive model related to drying temperature and equilibrium moisture content is established by using support vector machine technique. Also, free moisture content model and bound moisture content model are set up to analyze the removing condition of free water and bound water. Moreover, practical parameters selection for SVM model is investigated and an infinite impulse response filter technique is used to filter large noise of training data. Finally, simulation results are given to show the effectiveness of the proposed method.

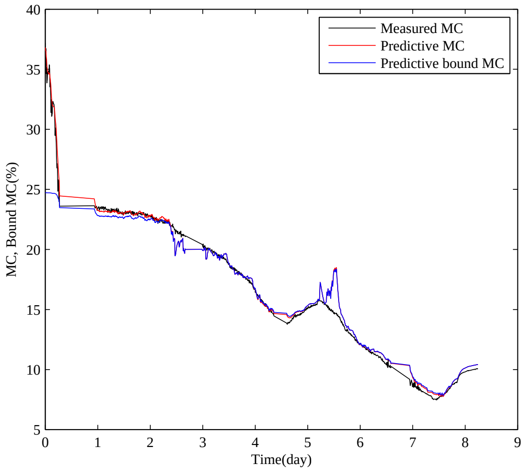

Figure 7. Bound MC predictive result

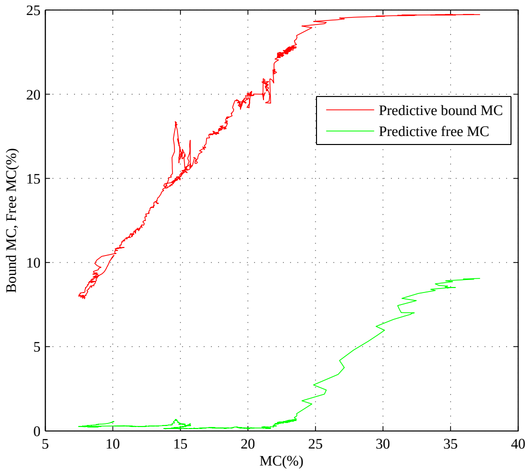

Figure 8. Free MC and bound MC

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