Development of Virtual Measurement Technology of Secondary Sodium Flow Rate

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The 'Virtual Measurement' method, utilizing neural networks that are trained with plant data, enables the indirect estimation of objective physical quantities even when plant signal are incomplete and/or when erroneous states of the plant are encountered.

This study applied the technique of virtual measurement to estimate sodium flow rate in the secondary heat transport system and proposed a framework for the isolation of erroneous estimates caused by faulty components.

As a result, it was demonstrated that, with the use of the virtual measurement method, credible measurements of objective physical quantities could be obtained even if under conditions where comprehensive information is lacking.

キーワード
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1. Introduction

Nuclear power plant operators are required to subjectively estimate the approximate values of some important physical quantities based on their expertise, when the quality of relevant measurement signals is degraded or completely lost. Accordingly, the indirect estimation of physical quantities from other information resource is a strongly desired for the operation of nuclear power plants including fast breeder reactors (FBR). This technology enables the estimation of some important but not directly observed quantities such as safety parameters.

This technology is also essential to increase the redundancy of instrument information in the methodology of analytic redundancy. However, the conventional technology of indirect estimation requires a complete physical model and a complete set of observed signals for the model to calculate the objective quantities. This restriction reduces the applicability of the technology in practice, because a complete model of the system and the precise condition of its applicability are difficult to obtain for large and complex systems like nuclear power plants. Moreover, the arrangement and the quality of the sensors in the system are not always sufficient for the purpose of conventional indirect...
estimation, since the specification of the instrumentation in the plants has not been originally designed for the technology.

The research activities on indirect estimation of physical quantities originated a new technique named 'Virtual Measurement'. It is based on the recent progress of software computing technologies such as neural network, fuzzy set theory and artificial intelligence, and enables estimation under ambiguous and incomplete information. This technique does not require any complete models nor complete sets of observed signals to obtain the indirect estimation of the objective quantities. It also has high robustness even in a degraded environment so that the feasible values of the objective quantities are estimated even under distorted and incomplete measurement environments without using any physical models. The feature of this technique will provide an efficient remedy to the limited applicability of the current indirect estimation methods. This technique is expected to support appropriate decision making by the operators by providing credible estimation of important physical quantities. One of the representative study on the technique of virtual measurement was performed by L. Tsoukalas et al. They applied multiple neural networks to obtain an experimental model of a valve opening in a plant, and estimated the value as some fuzzy numbers. Their method demonstrated high applicability even when deprived of some important observations and when anomalous states of the plant are encountered. Another study to apply the technique to sensor validation was carried out by Sakuma et al. It was to validate the output signals of sensors installed in a plant. Multiple virtual instruments consisting of neural networks were developed to estimate some sensor outputs by using signals from the other sensor. Consistency checking between the indirect estimation and the direct observation provides the information to validate each sensor.

However, an outstanding issue of indirect estimation by virtual measurement remains. When some mechanisms of the system on which a virtual measurement depends is disturbed or completely changed by some faults in the system, the estimated value of the objective quantity or parameter becomes no longer valid. Accordingly, the validity of the mechanisms relied upon by a given set of virtual measurements must be always monitored. Once some faults of the mechanisms are observed, the identification of the faulty mechanisms, i.e., diagnosis, and the isolation of the virtual measurements involving those faulty mechanisms must be conducted subsequently.

The work presented here proposes a set of possible schemes for the virtual measurements based on recurrent neural networks to measure the sodium flow rate in the secondary neat transport system (SHTS) of the Monju, and the framework for the diagnosis and the isolation of faulty virtual measurements. The feasibility of the proposed schemes and the framework is demonstrated through computer simulations using measurement signals related to with the SHTS circulation.

2. Method of Virtual Measurements

Most of the past works to develop virtual measurements utilized the conventional three layers feedforward neural networks. The advantages of this type of neural network are its simple implementation and the fast convergence in training. However, its ability to embed a given data is basically limited to the static relations among the data. As the virtual measurements should provide valid estimations of the objective quantities under dynamic changes of the plant state, this feature of the conventional approach can easily mislead the estimation when the plant state changes rapidly. Based on this consideration, we adopted the use of two layers recurrent neural networks called 'Elman networks'. The outline of this network is depicted in Figure 1. Multiple inputs are provided to each hidden unit from the input layer (arrows 1 in Figure 1). The output function of each hidden

![Figure 1 Schematic of the Elman Network](image-url)
unit is a tangent sigmoid function. The output, after delay of one time step, is fed back as an additional input to all the units in that layer (arrows Ⅰ in Figure 1). Also, the outputs from the hidden units are loaded to a output unit (arrows Ⅱ in Figure 1). This output unit is completely linear, and its output is the result of the entire neural network. The hidden units are highly expressive due to the feedback mechanism among the units. The function of the output unit is to take a weighted sum of all outputs of the hidden units and to adjust the bias level of the final output. This network has the following advantages.

1. The recurrent mechanism enables the learning of the highly dynamic features of a given data.
2. Any relations among the given data can be embedded if a sufficient number of units is provided in the first layer.

These features are considered highly desirable for the construction of virtual measurements functioning under dynamic and complex environments.

Efficient training algorithm necessary for the recurrent network because convergence speed of the training process is generally slow due to the compensation of the output change of each unit by the feedback effect. Accordingly we applied an advanced back propagation algorithm using the momentum method in concert with the adaptive learning rate method(D). In the momentum method, the rate of change of each weight in a given neural network is modified based on both of its past rate of change and the new rate of change evaluated by the ordinary back propagation rule. This mechanism has a tendency to prevent the convergence of the weights to a point of shallow local minin. In the adaptive learning rate method, the contribution ratio of the new rate of change of the weight over the past rate of change in the momentum method is tuned depending on the modeling error of a given network. When the error becomes larger, the contribution ratio is decreased to reduce the learning effect in the undesirable direction. Contrarily, when the error becomes smaller, the ratio is increased to accelerate the learning in the desirable direction. By the use of this training method, the Elman network could be trained to within a sufficient accuracy in a reasonable time period.

3. Schemes of Virtual Measurements

Possible schemes to estimate an objective quantity can be categorized into the following four principles.

① Direct measurement by a dedicated sensor
② Estimation based on a complete model
③ Estimation based on an incomplete model having well characterized physical relationship
④ Estimation based on an empirical model of some derivative relationship

The first principle is generally applied to actual power plants. The second is the scheme used in conventional analytical approach for the quantity estimation. The technique of virtual measurement can also use this principle, and the technique yields a significant advantage over the conventional framework, especially when the complete physical model is too complex and/or sensitive to error and noise in the measurements. Estimation based on an appropriate empirical model in the form of neural networks embedding the sampled data can reduce the computational load and enhance the robustness of the accuracy against measurement distortion. The third is a major principle of virtual measurements. An empirical model can provide valid estimation under limited operation conditions even if the model and measurements are incomplete. The forth principle is also applicable to estimate an objective quantity under a limited condition of operation. The adoption of the third and forth principles in the technique of the virtual measurements highly enhances the applicability of the technology of the indirect estimation under practical situations.

The schemes exemplified in our present study are applied to the estimation of the sodium flow rate in the SHTS of the Monju plant. The sodium flow rate is an important quantity to monitor the plant operation and safety. Figure 2 shows the

![Figure 2](image-url)
causal relations among the major physical variable regulating the flow of sodium in the SHTS. The master signal controlling the secondary sodium flow rate, MS, regulates the SCR voltage, V, and SCR frequency, F, of the 'Inverter & Main Power through components of in the 'Master Circuit' and 'Inverter Controller'. These quantities further regulate the torque, T, and rotation speed, R, of the 'Pump Motor' and 'Main Pump'. These quantities together with the pressure drop, 'SHTS', finally determine the coolant flow rate, FL. Also, these change the levels of sodium, Lp, and, Lo, in the 'Main Pump' and 'Pump Over Flow Column' (POFC), respectively.

Based on causal relations, the following five schemes can be utilized for virtual measurement to estimate the flow rate of sodium coolant, FL.

S1 Direct estimation from a sodium flow rate sensor, FL.
S2 Estimation from master control signal, MS
S3 Estimation from SCR frequency, F, and SCR voltage, V
S4 Estimation from pump rotation speed, R, and SCR current, I
S5 Estimation from sodium levels of pump, Lp, and of POFC, Lo

The scheme S1 is the adoption of the first principle. The scheme S2 is based on the second principle, since the sodium flow rate is completely determined by the master control signal if all components in Figure 2 are normal. The scheme S3 also belongs to the second principle, because the combination of F and V completely determines the state of 'Pump Motor', 'Main Pump' and 'SHTS', provided these components are functioning normally. The scheme S4 uses the second principle as well. The last scheme S5 is example of the forth principle, as the relations of Lp and Lo to FL are derived from empirical observations, and do not have clearly defined mechanistic models which relate the parameters.

Each scheme is applied to the following cases to evaluate their ability to estimate the objective sodium flow rate.

Case 1. A case of flow rate change from 50% to 100% and subsequently from 100% to 50% in 10% stepwise manner.
Sampling Rate: 1 sec (6301 time steps)

Case 2. A case of flow rate change from 0% to 100% in 10% stepwise manner.
Sampling Rate: 1 sec (12301 time steps)

The schemes S2 - S4 are tested using the case 1, and the last scheme S5 is tested using these of case 2. This is because the measurement data, Lp and Lo, were recorded only in the second case, while the other measurements were maintained only in the first case. The sodium flow rate directly measured by the scheme S1 in the first case is depicted in Figure 3. These data, after down sampled at every other 64th data points as shown in Figure 4, were used to train the networks of the schemes S2 - S4. After 200-300 times of the training iterations, the modeling errors less than 0.5% per a data sample. The performance of these virtual measurements is indicated in Figure 5 to 7. The solid trajectories give the estimated sodium flow rate, and the gray ones are the directly measured sodium flow rate from Figure 5. They show good agreement. Figure 8 shows the trajectories of the sodium flow rate and the sodium

![Figure 3 Direct Measurement of Secondary Sodium Flow Rate in Case 1](image)

![Figure 4 Data to Train Neural Networks in Case 1](image)
Figure 5  Comparison between Schemes S1 and S2

Figure 6  Comparison between Schemes S1 and S3

Figure 7  Comparison between Schemes S1 and S4

Figure 8  Direct measurement of Sodium Flow Rate (a) and Sodium Liquid Levels (b) in Case 2

Figure 9  Comparison between Schemes S1 and S5

levels, Lp and Lo, for Case 2. The solid line indicates the trajectory of Lp, and the gray line is that of Lo. Neither levels reflect the change in the sodium flow rate under 40% of flow rate, and have some response delay to the change in flow rate. These data, after down sampled at every other 64th data points, were used to train the network of this scheme. The performance of this virtual measurement is indicated in Figure 9. The solid line gives for the estimation, and the gray line is the direct measurement obtained through the scheme S1. Some significant errors are observed, especially after each stepwise flow change transients. This is because of the response delay of Lp and Lo. On the other hand, the estimation shows moderately good agreement even under 40% of flow rate. As the estimated trajectory roughly indicates the level of the sodium flow rate, this estimation also can be used to check the validity of the estimations of the other virtual measurements.

4. Framework of Diagnosis and Fault Isolation

For the isolation of faulty virtual measurements, the diagnosis of the virtual measurements based on mutual consistency checking is conducted. The generic procedure of the diagnosis consists of three stages\(^3\),\(^4\). First is to generate minimal conflicts based on the result of the consistency checking. Suppose a virtual measurement scheme, Si (i=1,...,m), assumes the validity of a set of
components, COMPS (Si). When we observe an inconsistency between the estimations of the different schemes, Si and Sj, the following logical disjunctive form can be made:

\[ V_{\lor c} = \text{COMPS}(Si) \lor \text{COMPS}(Sj) \land AB(c) \]  

(1)

The literal AB(c) stands for that the component c is faulty, and the symbol \( \lor \) expresses the disjunction (logical OR). This expression is valid, since at least one of the components in COMPS(Si) \( \lor \) COMPS(Sj) must be operating abnormally to cause the discrepancy between the estimations of the two schemes. When some inconsistencies are observed for multiple pairs of the schemes, the disjunctive form (1) is also derived for each inconsistency. If a disjunctive form involves all literals in another disjunctive form, the former one is removed since the latter shows more specific candidates of faulty components. A disjunctive form which does not involve any other disjunctive form is said to be at 'minimal conflict'. A state of minimal conflict gives the most specific candidates of faulty components in terms of the inconsistency between a given pair of schemes.

The next stage is to derive probable diagnoses based on these minimal conflicts. Given a set of minimal conflicts, the Cartesian conjunctions of the literals over the minimal conflicts are taken, and the conjunctive forms involving all literals in the other conjunctive forms are removed. The remained conjunctive forms are called 'minimal diagnoses'. As the operation of the Cartesian conjunctions is to take a literal AB(c) from each minimal conflict, the conjunctive forms stand for the interpretations of possible multiple faults of components. Accordingly, a minimal diagnosis which involves the minimal number of faulty components indicates a probable diagnostic solution. As the possibility of multiple faults is usually quite limited, diagnostic solutions involving the least number of literals are considered to be the most probable. These solutions are named 'minimum diagnoses'.

The third stage is to evaluate the credibility of each virtual measurement. Given a set of minimum diagnoses, the anomalous schemes of virtual measurements are identified for each minimum diagnosis. The identification procedure is quite simple as a scheme Si is judged to be anomalous when COMPS(Si) contains any abnormal components in the minimum diagnosis. Scheme which are judged more often to be anomalous by the minimum diagnoses are considered to be less credible.

In case of our current example, the sets of components associated with the schemes S1-S3 are summarized as follows based on Figure 2:

- **COMPS(S1)** = (Sodium Flow Sensor)
- **COMPS(S2)** = (Master Circuit, Inverter Controller, Inverter & Main Power, Pump Motor, Main Pump, SHTS)
- **COMPS(S3)** = (Frequency Sensor, Voltage Sensor, Inverter Controller, Inverter & Main Power, Pump Motor, Main Pump, SHTS)
- **COMPS(S4)** = (Rotation Speed Sensor, Current Sensor, Inverter & Main Power, Pump Motor, Main Pump, SHTS)
- **COMPS(S5)** = (Pump Level Sensor, FOPC Level Sensor, Main Pump, SHTS, FOPC)

The sensors are added as components to include the possibility of sensor faults.

For example, consider the scenario if inconsistencies in pairs 'S1 & S3' and 'S2 & S3'. In this case, the following disjunctive forms are derived based on the sets COMPS(S1), COMPS(S2) and COMPS(S3):

- **S1 & S3** \( \land (\text{AB}(\text{Sodium Flow Sensor}) \lor \text{AB}(\text{Frequency Sensor}) \lor \text{AB}(\text{Voltage Sensor}) \lor \text{AB}(\text{Inverter Controller}) \lor \text{AB}(\text{Inverter} & \text{Main Power}) \lor \text{AB}(\text{Pump Motor}) \lor \text{AB}(\text{Main Pump}) \lor \text{AB}(\text{SHTS}),

- **S2 & S3** \( \land (\text{AB}(\text{Frequency Sensor}) \lor \text{AB}(\text{Voltage Sensor}) \lor \text{AB}(\text{Inverter Controller}) \lor \text{AB}(\text{Inverter} & \text{Main Power}) \lor \text{AB}(\text{Pump Motor}) \lor \text{AB}(\text{Main Pump}) \lor \text{AB}(\text{SHTS})

These forms do not involve one another. Thus, they are already at minimal conflicts. By taking the Cartesian conjunctions of these minimal conflicts and testing only on minimal diagnosis, we obtain the followings:

- \( \text{AB}(\text{Frequency Sensor}), \text{AB}(\text{Voltage Sensor}), \text{AB}(\text{Inverter Controller}) \).
AB(Inverter & Main Power), AB(Pump Motor), AB(Main Pump), AB(SHTS), AB(Sodium Flow Sensor) \land AB(Master Circuit).

As the minimum number of literals involved in each solution is one, the solution involving the simultaneous failure of two components is removed, and the minimum diagnoses are derived:

- AB(Frequency Sensor), AB(Voltage Sensor), AB(Inverter Controller), AB(Inverter & Main Power), AB(Pump Motor), AB(Main Pump), AB(SHTS).

For each minimum diagnosis, the following inferences regarding potential anomalous virtual measurements are performed:

- AB(Frequency Sensor) \rightarrow AB(S3),
- AB(Voltage Sensor) \rightarrow AB(S3),
- AB(Inverter Controller) \rightarrow AB(S2) \lor AB(S3),
- AB(Inverter & Main Power) \rightarrow AB(S2) \lor AB(S3) \lor AB(S4),
- AB(Pump Motor) \rightarrow AB(S2) \lor AB(S3) \lor AB(S4),
- AB(Main Pump) \rightarrow AB(S2) \lor AB(S3) \lor AB(S4) \lor AB(S5),
- AB(SHTS) \rightarrow AB(S2) \lor AB(S3) \lor AB(S4) \lor AB(S5).

Consequently, the scheme S1 provides the most credible value of sodium flow rate. This information is reflected to select the credible estimations among multiple estimations.

5. Discussion

The main purpose of the study by L. Tsoukalas et al. was to develop robust virtual measurement. However, their framework does not involve the diagnosis and fault isolation process. Accordingly, the robustness of their scheme is limited to small scale disturbances. Disturbance over a certain scale, such as severe faults of components may, cause some significant estimation errors. Another study by Sakuma et al. proposed the combined use of virtual measurements and diagnosis. However, their main purpose was for sensor validation, and the diagnosis was not used to enhance the robustness of the virtual measurement system.

Because the aims of virtual measurements are the indirect estimation of important quantities and to improve the robustness of the estimation, enhancement of the robustness by the introduction of the diagnosis process may significantly increase the applicability of this technique. Our work has addressed this important issue.

6. Conclusion

The technique of virtual measurement is a valid method to support operators in making decisions by providing credible estimations of interested but not directly measurable variables. Furthermore, this technique is based on the recent progress of neural network research and does not require a comprehensive model nor a complete set of observed signals to obtain the indirect estimation of the desired quantities.

The objectives of this study are to propose a set of possible schemes for virtual measurements based on the use of recurrent neural networks which enables the learning of highly dynamic features of a given data set and a framework for the isolation of faulty virtual measurements.

For the first objective, the possible virtual measurement schemes for use to estimate an objective quantity can be categorized to fall under four principles (specifically: direct measurement by a dedicated sensor, estimation based on a complete model, estimation based on an incomplete model having well characterized physical relationship, estimation based on an empirical model of some derivative relationship). In this study, based on the causal relations used to determine the secondary sodium flow rate, five virtual measurement schemes were devised for estimations of the sodium coolant flow rate. Each scheme was applied to two test cases to evaluate its basic ability to correctly estimate the sodium flow rate. The estimated and directly measured sodium flow rates show good agreement.

The second objective was also achieved by introducing the following method. In the first stage, estimates of the objective quantity by the different schemes are compared. The next stage is to generate a set of minimal conflicts based on the result of the consistency checking of the assumptions made by each scheme. In the third stage, the minimum diagnoses are used to evaluate the credibility of each virtual measurement. Using this method, a systematic approach for fault
isolation has been found.

Associated with these objectives and results, the following topics still remain for future study:

1. Systematic and robust approaches for consistency checking must be developed.

2. Appropriate method to fuse the values of the objective quantities estimated by the remaining consistent virtual measurements must also be developed.

3. In addition, by taking into consideration also the paths of the causal relations, we may be better able to identify faulty components and isolate faulty virtual measurements.

References


