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인공신경망 기반 실시간 소양강 수온 예측

Artificial Neural Network-based Real Time Water Temperature Prediction in the Soyang River

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Abstract - It is crucial to predict water temperature for aquatic ecosystem studies and management. In this paper, we first address challenging issues in predicting water temperature in a real time manner and propose a distributed computing model to address such issues. Then, we present an Artificial Neural Network (ANN)-based water temperature prediction model developed for the Soyang River and a cyberinfrastructure system called WT-Agabus to run such prediction models in an automated and real time manner. The ANN model is designed to use only weather forecast data (air temperature and rainfall) that can be obtained by invoking the weather forecasting system at Korea Meteorological Administration (KMA) and therefore can facilitate the automated and real time water temperature prediction. This paper also demonstrates how easily and efficiently the real time prediction can be implemented with the WT-Agabus prototype system.

Key Words : Real time environmental prediction, Water temperature, Artificial neural networks, Cyberinfrastructure.

1. Introduction

Water temperature is one of main variables in water quality that influence many chemical processes as well as biological conditions and behaviors [1]. Therefore, the aquatic ecosystem management often require prediction models for water temperature. For example, real time water temperature prediction provides scientists and environmental policy makers with new opportunities for managing water quality proactively and dealing with unexpected or abrupt environmental changes promptly. In environmental studies, there are lots of research efforts on the development of such prediction models and their application for environmental analyses, planning, and decision-making [1-13]. However, these research efforts are usually not intended for real time prediction.

In this paper, we present an Artificial Neural Network (ANN)-based water temperature prediction model developed for the Soyang river that can predicts water temperatures only by weather forecast data. Such forecast data can be easily obtained by invoking the weather forecasting system at Korea Meteorological Administration (KMA). Therefore, this ANN model is designed to facilitate the automation of data collection at run time. Then, we also present a cyberinfrastructure system called WT-Agabus to run such prediction models in an automated and real time manner.

Agabus is our ongoing research effort to develop a stream processing-based real time prediction system for scientific and engineering applications. WT-Agabus is a part of the development effort aimed specifically at real time water temperature prediction. Our development strategy for Agabus is not to implement the system from scratch but to integrate available system middleware as much as possible. This strategy allows us to reduce implementation work significantly and to design the system to be composable and extensible. In the development of WT-Agabus, we use the sensor network middleware called CSN and the sensor data repository system called S4EM which are already developed as separate projects [14, 15, 16]. In addition, we use the stream processing-based prediction model simulation system called PS3.

This paper is organized as follows. In Section 2, we raise challenging issues and propose a distributed computing model intended to address these issues. In Section 3, we present a water temperature prediction model based on Artificial Neural Networks (ANN). The system design of

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WT-Agabus is explained in Section 4. Section 5 explains the system implementation and shows the performance evaluation of the water temperature prediction model. In Section 6 and 7, we discuss related work and conclude this paper. This paper is an extended version of a preprint paper available at arXiv.org (a repository of electronic preprints of scientific papers) [17].

2. Distributed Computing Model for Real Time Environmental Prediction

Real time environmental prediction such as the prediction of water temperature in rivers raises serious challenges to both environmental scientists and IT professionals as follows. First, It requires a variety of technologies and systems including monitoring (e.g., sensor networks), data management (e.g., the management of time series data such as sensor data), the development of prediction models (e.g., Artificial Neural Networks), the execution of prediction models (e.g., analytics engines), and event notification. Therefore, it is very interdisciplinary and involves collaboration among experts from various domains.

Second, these technologies and systems must be seamlessly integrated and run as a single distributed system at run time. However, they are often independently developed in different research areas and not intended for such integration.

Finally, if prediction is required in a real time manner, then prediction models must be designed not to depend on input data that is impossible or really difficult to collect in an automated and real time manner. In other words, the developers of prediction models must consider real world environments where prediction models are actually used.

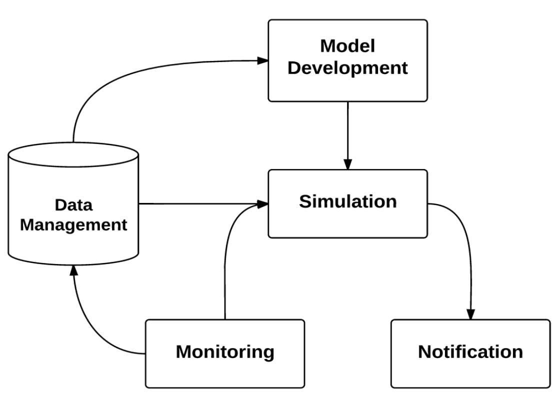

그림 1 실시간 수온 예측의 컴퓨팅 구조
Fig. 1 The Computing Structure of Real Time Water Temperature Prediction

In this paper, we propose a distributed computing model designed to address these challenges efficiently. This computing model identifies major system components and how to integrate them in a real time manner. Its computing structure is shown in Fig. 1. The computing model represents real time environmental management integrating a number of real time computational activities:

- Monitoring. Prediction models (e.g., artificial neural network models) are developed by analyzing datasets from monitoring. In addition, the execution of prediction models may also depend on data from real time monitoring as input data to generate prediction values.
- Data Management. A lot of data from environmental monitoring is required to develop, evaluate, validate and improve prediction models.
- Simulation. Real time environmental prediction requires the effective runtime execution (i.e., simulation) system to support various prediction models. There are already a variety of water temperature prediction models available and on-going research efforts for new models.
- Notification. Prediction results (i.e., water temperature data predicted for the future) should be promptly delivered to human users or other computer systems that decide or take actions based on prediction results. Humans or computer systems involved in environmental management need to be notified of environmental events in order to work in a proactive way.
- Integration. These system components should be integrated over data streams. Prediction is not one time operation but a series of operations over the streams of input data.

Fig. 1 illustrates a distributed computing model for real time environmental prediction. The arrows represent data streams between system components.

3. Artificial Neural Network-based Water Temperature Prediction

In this section, we present an ANN-based water temperature prediction for the Soyang River that is based on the computing model given in Section 2. The computing model requires prediction models to use only input variables whose values can be collected in an automated and real time manner. The ANN-based water temperature prediction model uses only weather forecast data available online from KMA. Specifically, the prediction model uses only air temperature and rainfall as the input variables and water temperature as the output variable.

3.1 Sampling

The water temperature prediction model is developed for the Soyang River basin located in a mountainous district in South Korea. The Soyang River is geographically and hydrologically summarized as follows. It is 77km-long and a steep river system (the altitude difference of the watershed is from 200m to 1,700m). The ratio of water flow rate on dry days and rainy days are greater than 300 due to the effect of summer monsoon. On dry days water flow is slow and the temperature is well equilibrated with air temperature. But on rainy days, the water is cooler than air temperature, because water flows faster and it cannot have enough time to be equilibrated with air temperature. Therefore, the cooling effect of high altitude air is exerted to the downstream reaches.

This study uses the water temperature dataset collected at a point of inflow between the Soyang River and Lake Soyang from 1991 to 2009. The water temperature data was recorded at depth of 1m from the surface because of the fast water flow speed. This study also uses the meteorological dataset obtained from the Inje Meteorological station, Korea from 1991 to 2009. The distance between the meteorological station and the water temperature monitoring site is less than 3 km. We use the hourly estimates of air temperature (TM) and rainfall (RF) data.

3.2 Model Development

3.2.1 Data preprocessing

In the development of the water temperature prediction model, this study uses the air temperature and the rainfall as the input variables and the water temperature as the output variable. The entire dataset consists of 1126 records in this study. The first 790 observations were used to train the prediction model. The remaining observations were used to test the prediction model.

To generate the input variables, we investigate the correlations coefficients with an imposed time lag. We assume that previous meteorological states (e.g., air temperature, rainfall) influence the current water temperature [6-13]. Specifically, we assume that Y_t is related to X_{t-k} where Y_t and X_{t-k} are defined to be the hourly water temperature at hour t and meteorological variables at hour $t-k$, respectively. The association between the values of Y_t and X_{t-k} is measured by comparing the cross-correlation between Y_t and X_{t-k} when k varies from 0 to 24. The cross-correlation based on the Pearson correlation function is calculated by [18,19].

$$\widehat{\rho_{YX}}(k)=\begin{cases}\dfrac{\sum_{t=1}^{N-k}\left(Y_t-\overline{Y}\right)(X_{t+k}-\overline{X})}{Ns_Ys_X}, & k\geq 0\\ \dfrac{\sum_{t=1-k}^{N}\left(Y_t-\overline{Y}\right)(X_{t+k}-\overline{X})}{Ns_Ys_X}, & k<0\end{cases}$$

In this equation, s_Y and s_X are the sample standard deviations of the time series Y_t and X_t (weather variables), respectively. We use the cross-correlation to calculate the time lag of between the air temperature and the water temperature. It is found to be 17 hours. So, the air temperature (TM), the 17 hour-earlier air temperature, and the current rainfall (RF) are selected as input variables.

To estimate the prediction model performance, the root-mean-square error (RMSE), the Nash Coefficient (NASH), the correlation coefficient (R), and the index of agreement (IA) are used [5,20,21].

- RMSE= $\sqrt{\sum_{i=1}^{N}(O_i-P_i)^2/N}$ where N is the number of hourly water temperature observations, O_i the observed hourly water temperatures, and P_i the predicted hourly water temperature.
- Nash= $1-\left\{\sum_{i=1}^{N}(O_i-P_i)^2/\sum_{i=1}^{N}(O_i-\overline{O})^2\right\}$ where $\overline{O}$ is the mean hourly water temperatures for the period N.
- R= $\sum_{i=1}^{n}\left(O_i-\overline{O}\right)\left(P_i-\overline{P}\right)/\sum_{i=1}^{n}\left(O_i-\overline{O}\right)^2\sum_{i=1}^{n}\left(P_i-\overline{P}\right)^2$
- IA= $1-\left\{\sum_{i=1}^{n}(P_i-O_i)^2/\sum_{i=1}^{n}(\left|P_i-\overline{O}\right|+\left|O_i-\overline{O}\right|)^2\right\}$. The IA is a relative measure which is suitable to evaluate different models to be compared using different data set.

3.2.2 Artificial Neural Network

A multi-layer ANN uses an approach that creates models of a system state using non-linear combinations of the input variables [22,23,24]. The ANN model used in this paper is a feed-forward network with sigmoid functions in the hidden layers and a linear activation function in the output node in MATLAB ver. 2012a. The ANN model has only one hidden layer because according to Bishop's research, multiple hidden layers do not, usually, show significantly better performances than one hidden layer [22]. The ANN is trained by using a back propagation algorithm (a gradient descent technique) that minimizes the network error function [25].

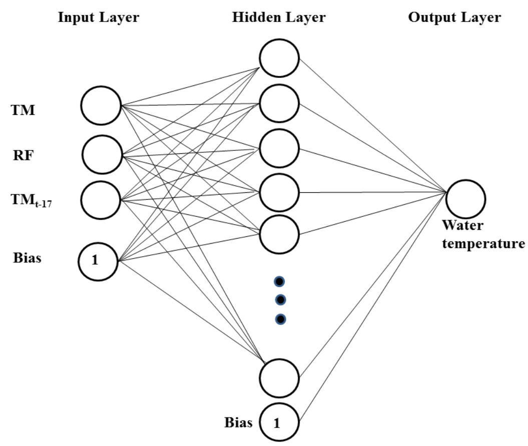

그림 2 Feed-forward 인공신경망
Fig. 2 Feed-forward Artificial Neural Network

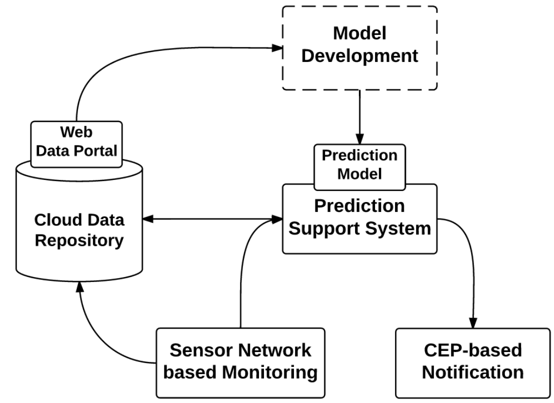

그림 3 실시간 환경 예측을 위한 시스템 구조 개념도
Fig. 3 Conceptual system architecture for real time environmental prediction

The ANN requires the learning rate, the number of nodes in a single hidden layer, and the maximum number of training epochs. In this paper, we applied the optimal number error approach [26]. The number of nodes in the hidden layer was varied between 5 and 25 and the learning rate was varied from 0.01 to 1.0 in increments of 0.05. For each configuration, the mean square error (MSE) between the model output and the measured data was computed. Having 10 neurons in the hidden layer and 0.55 learning rate resulted in the maximum model performance with respect to MSE. As shown in Fig. 2, The final ANN structure has three input variables with one node accounting for bias, ten hidden neurons with one node accounting for bias, the 0.55 learning rate, and one output variable of the output layer.

4. Cyberinfrastructure-based Environmental Prediction Support System

4.1 System Architecture

In this section, we present the architecture of the WT-Agabus real time water temperature prediction system designed as a cyberinfrastructure to integrate a collection of existing system middleware. WT-Agabus is designed to support a variety of prediction models by customization. Fig. 3 illustrates the WT-Agabus architecture. Its major system components are:

- PS3 (Prediction Model Simulation System over Data Streams) for the real time execution of prediction models. It is designed to run prediction models in an automated, real time manner. It can be configured to support a variety of prediction models.
- CSN (Conceptually Manageable Sensor Network) for real time monitoring. It is designed as a sensor network based monitoring system.
- S4EM (Simple Sensor Data Stream Management System for Environmental Monitoring) for data management. It is desigend as a cloud data repository.
- Esper for CEP-based Notification. Esper is an open source Complex Event Processing engine. It is designed to support event detection and notification on sensor data streams.
- Web Data Portal (WDP). WDP helps scientists to access to the archive of monitoring data and prediction results. Scientists can use WDP for the development and improvement of prediction models.

All of these middleware systems are based on stream processing and management. Therefore, they are integrated according to the stream processing model [5,27]. In this section, we briefly introduce CSN and S4EM. Since we are currently using basic and simple CEP features in Esper, we do not explain Esper in this paper. However, we plan to develop a notification system on top of Esper [28].

4.2 CSN: Conceptually Manageable Sensor Network

In WT-Agabus, we use CSN for real time monitoring [15]. CSN is our separate project for the development of a general-purpose sensor network middleware. As shown in Fig. 4, it is designed to facilitate the conceptual management of sensor networks and the easy application development.

In CSN, each sensor is managed as a logical data stream and implemented as a message queue. Sensors are accessed and shared via message queues according to the publish/

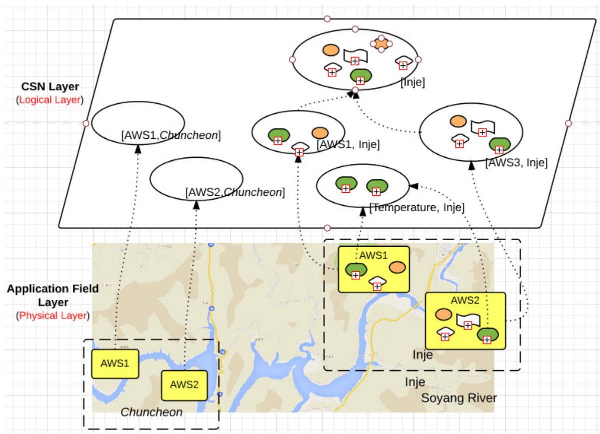

그림 4 CSN을 위한 시스템 모델
Fig. 4 System Model for CSN

subscribe model. Sensors simply send their data out by publishing them to their message queues. Applications can access data from sensors by subscribing their message queues. This design makes applications decoupled from sensors and greatly facilitates the development of applications.

In addition to the publish/subscribe model based communication, the CSN runtime system also supports a simple TCP/IP socket based communication. Sensors can simply send their data to the socket and then the CSN runtime system publishes their data for the behalf of those sensors. This communication method is intended for those sensors that cannot communicate according to the publish/ subscribe model.

The current design of the CSN system also supports other computer systems as a kind of virtual sensor as long as those systems are considered to generate data streams.

4.3 S4EM: Simple Sensor Data Stream Management System for Envionmental Monitoring

S4EM is designed to manage data streams from sensors [14,16]. S4EM is our separate project for the development of a general-purpose sensor data management middleware (data repository). In S4EM, a sensor data stream is simply a sequence of data values from a sensor and can be appended with new values until the data stream is explicitly closed. Therefore, a sensor data stream in S4EM is an infinite sequence of numeric data values. Therefore, the S4EM data repository consists of only a number of sensor data streams. S4EM currently assumes the type of data from a sensor to be numeric and the data is associated with time-stamps. We plan to support data to be of other types.

S4EM is currently implemented as a cloud SaaS service on top of the Google Datastore (PaaS). It provides a number of sensor data stream management services: create, append, search, retrieve, delete, and download. These services can be invoked by Web Browsers because they are implemented as Servlet programs. Since both CSN and S4EM assume data streams as the primary data object, they can be easily integrated according to the stream processing model [15,16]. The metadata model is designed to facilitate the analysis of sensor data. The current data model is based on the VEGA model developed by the Global Lake Ecological Observatory Network (GLEON) [29,30].

4.4 PS3: Prediction Model Simulation System Over Data Streams

The main features of the PS3 system are as follows:

- Heterogeneous Prediction Models. There are a number of prediction models based on various methods such as Artificial Neural Networks [31], Hidden Markov Models [32], and Genetic Algorithms [33]. These models are implemented by model development tools such as MATLAB or R. These models can be manually programmed. PS3 intends to support them in a uniform and configurable way.
- Heterogeneous Simulation Tools. There are a number of simulation tools to run prediction models. They include MATLAB and R. PS3 intends to support them in a uniform and configurable way.
- Stream Processing-based Continuous Simulation of Prediction Models. PS3 runs a prediction model according to the stream processing model [34]. In this model, PS3 assumes data streaming from monitoring systems (e.g., a CSN system) and iterates the simulation of the model with

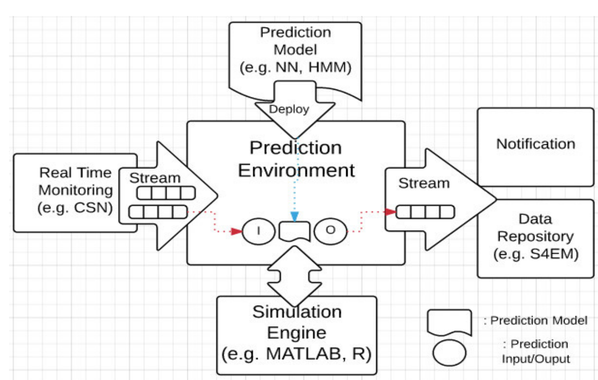

그림 5 스트림 처리 기반 예측 모델의 연속적 모사
Fig. 5 Stream Processing-based Continuous Simulation of Prediction Models

data values in data streams. When it access data streams, PS3 uses Esper with rules in EPL (Event Processing Language) to specify how to extract data for input variables from data streams. PS3 also sends prediction results out as data streams to a notification system or other applications. Fig. 5 illustrates the stream processing-based simulation.

5. Implementation and Experiments

5.1 The Current prototype implementation of WT-Agabus

In this section, we explain the current prototype implementation of the WT-Agabus system. The implementation is shown in Fig. 6. The WT-Agabus prototype runs the prediction model explained in Section 3 and receives input data from KMA (Korea Meteorological Administration).

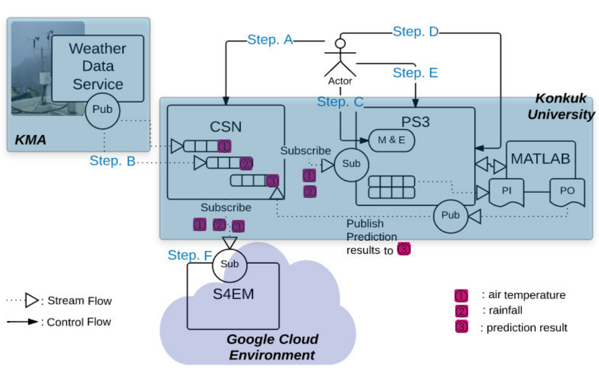

그림 6 WT-Agabus 프로토타입의 현재 실행시스템 구조

Fig. 6 Runtime Structure of the Current Prototype of WT-Agabus

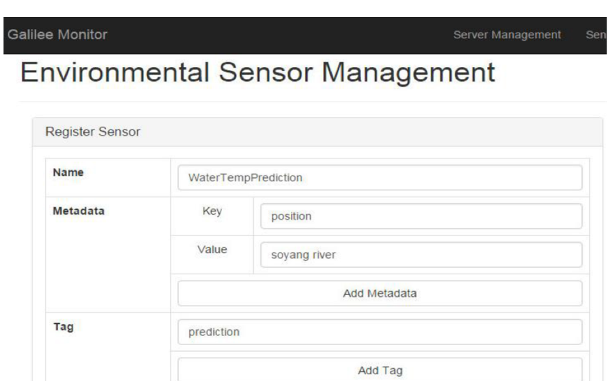

그림 7 CSN의 센서 등록 창

Fig. 7 Sensor Registration Window in CSN

An experiment with WT-Agabus is explained as follows. First, three sensors are registered and three data streams are created for those sensors in the CSN system. Currently, two sensors from Korea Meteorological Administration (KMA) are air temperature and rainfall. These sensors are numbered 1 and 2. The other sensor numbered 3 is virtual represents prediction results (i.e., water temperature) from PS3. In this implementation, we assumed virtual sensors for prediction results in such way that prediction models are considered as those virtual sensors. Fig. 7 shows the snapshot of the sensor registration window in CSN.

Second, data are read from two KMA sensors and they are published to the CSN system. KMA does not allow other systems to access their sensors directly, but provides RESTful web services for access to data from those sensors. The RESTful interface is explained in Table 1 and Table 2. Currently, KMA provides data about ten weather parameters such as temperature, rainfall, wind speed and wind direction. We implemented a system to read data from sensors via the RESTful web services and to publish data to CSN.

Third, the prediction model (given in Section 3) is registered and a simulation tool (MATLAB) is deployed in the PS3 system. The information about the prediction model and the simulation tool is given to PS3. PS3 provides the RESTful interface for the registration of prediction models and simulation tools. The interface is given in Table 3.

표 1 날씨 데이터 서비스에 대한 요청 인자들

Table 1 Request Parameters for Weather Data Service

Parameter	Sample Data	Introduction
base_date	20121206	The rises.
base_time	1100	The time
Nx	1	The spot X coordinate
Ny	1	The spot Y coordinate

표 2 날씨 데이터 서비스에 대한 응답 인자들

Table 2 Response Parameters for Weather Data Service

Parameter	Sample Data	Introduction
resultCode	0	Result-code
resultMsg	OK	The result message error message
numOfRows	10	One fruit bearing tree
pageNo	1	Page number
totalCount	10	The number of aggregated result
category	LGT	Data division code
obsrValue	-1	The real condition value

표 3 예측 모델과 모사 도구 관리를 위한 인터페이스
Table 3 Interface for Managing Prediction Model and Simulation Tool

#	Action	Method	Resources
1	Register the prediction model	PUT	/node/models
2	Get the prediction model	GET	/node/models/[mid]
3	Remove the prediction model	DELETE	/node/models/[mid]
4	Register the simulation tool	PUT	/node/engines
5	Get the information of simulation tool	GET	/node/engines/[eid]
6	Remove the simulation tool	DELETE	/node/engines/[eid]

표 4 입력 데이터 생성을 위한 EPL 규칙들
Table 4 EPL Rules for Input Data Generation

Stream in CSN	EPL Statements	Idx
air temperature	SELECT id, timestamp, avg(value) FROM Temperature.win:time(1 hour)	0
	SELECT id, timestamp, avg(value) FROM Temperature.win:time(17 hour) output snapshot every 1 hour	2
rainfall	SELECT id, timestamp, avg(value) FROM Rainfall.win:time(1 hour)	1

표 5 예측 관리를 위한 인터페이스
Table 5 Interface for Managing Prediction

#	Action	Method	Resources
1	Register Prediction Mode [mode]: prediction type 1:On_demand, 2: Scheduled. 3: Data_driven [interval]: interval time to re-run prediction model	POST	/node/prediction?mode=1&time=t&interval=3600
2	Start Prediction	POST	/node/prediction?action=start
3	Stop Prediction	POST	/node/prediction?action=stop

Fourth, three data streams (created in the first step) and stream processing rules (i.e., EPL statements) for input data are registered in the PS3 system. PS3 reads data from two data streams in CSN by subscribing their data streams. PS3 publish prediction results to the other data stream in CSN. Table 4 shows the EPL rules for input data generation.

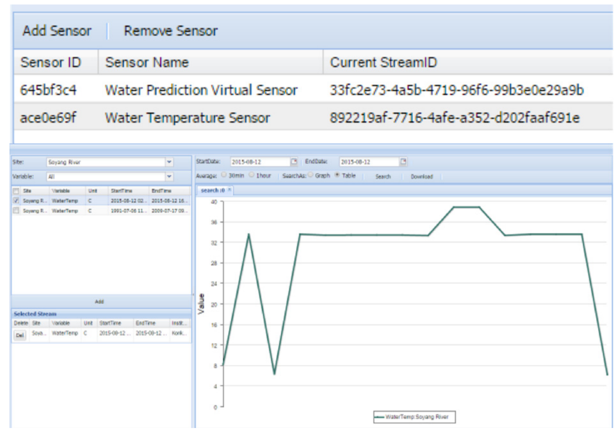

그림 8 (a) 센서 관리창, (b) 데이터 스트림 관리 창, (c)예측 결과를 위한 검색 및 다운로드 창
Fig. 8 (a) Sensor Management Window, (b) Data Stream Management Window, (c) Search and Download Window for Prediction Results

Fifth, the prediction service is started with a prediction schedule mode. The prediction schedule mode is currently set to the time scheduled mode. Table 5 shows interface for managing prediction.

Finally, three data streams (created in the first step) in CSN and prediction results from PS3 are stored in S4EM. Fig. 8 shows the snapshots of the S4EM windows.

5.2 Evaluation of the Water Temperature Prediction Model

The performance of the water temperature prediction model was evaluated. The meteorological properties and the water temperature at the monitoring site are provided in Table 6. High variability was observed in both RF and WT.

표 6 실험 기간 동안의 기상/수온 데이터의 평균과 표준편차
Table 6 Mean and Standard Deviation Values of Meterological Characteristics and Water Temperatures during the Experimental Periods

	TM. (˚C)	RF. (mm)	WT. (˚C)
Mean±std.	17.26±7.65	1.64±4.92	16.89±5.83
Ranges	-11.5~30.7	0~66	-12.3~28.8

According to the evaluation results, the ANN model showed good performances, overall. Table 7 shows the values of IA, R, RMSE, and NASH that are 0.92, 0.81, 3.15, and 0.64, respectively. However, the ANN models showed different performances for different value ranges. As shown in Fig. 9, the ANN model usually predicted well for low and average values, while it did not predict high values less accurately. The ANN model seems to over-estimate water temperatures for a high range of values.

Although the performance of the ANN model could be improved by adding more input variables, that will be likely to complicate the automated, real time collection of data for input variables.

표 7 인공신경망 모델 성능 통계
Table 7 ANN Model performance statistics

	MEAN	STD	RMSE	NASH	IA	R
ANN	16.91	5.22	3.15	0.64	0.92	0.81

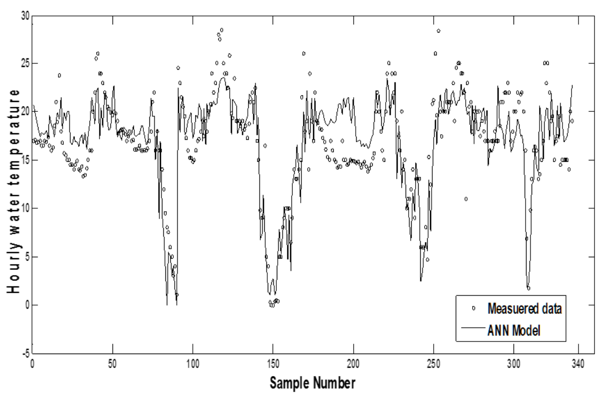

그림 9 인공신경망으로 얻어진 소양강 수온 관측과 예측
Fig. 9 Measured and Predicted Water Temperature in the Soyang River Obtained by ANN

6. Related Work

There are a number of research work on water temperature prediction models such as statistical models and deterministic models [4-13]. These studies are usually aimed only at the achievement of higher prediction accuracies and basically carried out as theoretical research. This paper is aimed at the development of a practical water temperature prediction model that can be effectively applied to a real world prediction system. Therefore, input variables are chosen not only for the prediction accuracy but also for the automated and real time data collection. Furthermore, this paper presents an actual ICT system to run such prediction models in an automated, and real time manner.

There are many research projects on sensor networks and cloud databases [15,35,36,37]. These projects are usually aimed at individual middleware systems. This paper addresses issues in integrating those technologies into a cyberinfrastructure for real time prediction and presents an distributed computing system designed as a cyberinfrastructure to integrate system middleware such as sensor networks, a data repository, and a prediction support system.

There are active ongoing research activities on distributed streaming processing systems [27,28,34]. But they focus on technologies for processing data streams efficiently. However, this paper addresses issues in integrating streaming processing into application-specific computations such as prediction.

7. Conclusion

The prediction of water temperature is crucial for aquatic ecosystem studies and management. In this paper, we raised challenging issues in real time environmental prediction and proposed a distributed computing model to address these challenges. Then, we presented a Artificial Neural Network (ANN)–based prediction model for water temperature in the Soyang River that is designed to facilitate real time prediction. For this reason, the ANN model uses only weather forecast data available online from Korea Administration Agency (KMA). In spite of its simple design, the ANN model, overall, showed reasonably good performances, according to performance evaluation results.

In addition to the ANN-based water temperature prediction model, we also presented a cyberinfrastructure system called WT-Agabus to run such prediction models in an automated, real time manner. WT-Agabus is designed to integrate existing system middleware such as sensor networks (CSN), a cloud sensor data repository (S4EM), the prediction model simulation system (PS3), and the Esper complex event processing system.

Finally, we explained how the real time water temperature prediction can be implemented with the current WT-Agabus prototype system. This experiment showed that such real time prediction can be easily and efficiently supported on a cyberinfrastructure like WT-Agabus.

감사의 글

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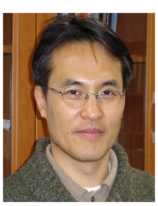

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