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Original scientific paper

Development of a Precipitation Prediction Model Using Water Resource Measurement Data

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Abstract: In response to the pressing global issue of water scarcity, numerous studies are under way both domestically and internationally to develop water-saving technologies and ensure clean water supply. These efforts heavily rely on water resource measurement data obtained from various sensing instruments operated by government and local agencies. These data are stored in servers and utilized for real-time predictive analyses and services. However, a challenge arises from the unrefined and fragmented nature of the data due to variations in sensing instruments and collection procedures. To address this issue and enable efficient big data analysis of water resource data, this paper introduces a novel approach. It presents the Smart Water Grid-based model for storing and classifying water resource measurement data, along with a comprehensive methodology for constructing a robust big data framework. By implementing this model, researchers and practitioners can enhance the effectiveness of their analyses and derive valuable insights from water resource data, contributing to the development of sustainable water management strategies.

Keywords: big data; data classification; multidimensional cube; smart water grid; water resource

1 INTRODUCTION

The Smart Water Grid Research Center in Korea analyzed and collected data on "Regional Water Shortage Risk Assessment System Development", which has vast informational value. Generally, data types are divided into structured and unstructured ones, but the back data secured by the Smart Water Grid Research Center is the former requiring quantitative measurement. It includes instrumentation data for Yeongjong Island reservoir - the area selected for the application of a complex-type system, daily demand calculation data for living, industrial and agricultural water in Yeongjong Island, and hydrological data applied to climate change scenarios [1, 2]. For such data, the accuracy of analysis and utilization may depend more on data quantity and size than the method of data instrumentation and collection [3-6].

From advanced cases of water management system development, we can see that instrumentation data focuses on the management, classification, and utilization of exponentially increasing historical data [7-10]. The analysis data secured by the Smart Water Grid Research Center covers agricultural water intake facilities, basic environmental facilities, and reservoir facilities. It is necessary to establish an environment suitable for data storage and predictive analysis based on best practices by utilizing the instrumentation data derived from such an infrastructure environment and preparing a methodology to utilize the analyzed data. In addition, as informatization develops, the use of resource environment and climate change measuring instruments has become common, which leads to a rapid increase in data accumulation [11, 12]. This situation enables us to data utilization that has not been attempted before and increases the potential value and influence of data. Therefore, if the accumulated instrumentation data is utilized well, it is possible to create an important value that can present a big data analysis methodology suitable for predicting flooding and securing safety in response to climate change. Since the importance and use-value of big data are increasing worldwide and expanding into multiple fields, it is recognized as an engine that will create future social values in the future and is designated as national competitiveness in national policies [13-15].

In this regard, this study selected a specific area based on the instrumentation and precipitation data systematically operated and managed by the Smart Water Grid Research Center. Through this, this study was to develop an efficient predictive model that can reduce the damage from flooding due to climate change.

This study aimed to set up concrete data pre-processing that fits the analysis target. Although fast collection and management technology of massive data in real-time has significantly developed and been handed to computers and automation tools, most of the data pre-processing field yet remains in human territory. In case of unlabeled data utilized for data analysis, the reliability of the analyzed data is determined by how elaborate the preprocessing technique is. Various earlier data analysis studies utilized different pre-processing techniques according to the analysis target. However, the general pre-processing technique has limits in securing precipitation prediction data. Thus, this study was designed to apply the earlier pre-processing technique, introduce a new and original pre-processing technique, and increase the reliability of the precipitation prediction.

The procedure presented in this paper is as follows. First, build a big data platform that can secure, collect, and manage historical water resource and precipitation data of the areas located on the coast of Korea.

Second, to increase the accuracy of the precipitation data, it proposes a new data classification model that can remove missing values and outliers. Third, based on the classification model, it secures the reliability of the precipitation prediction by comparing and conforming (matching) the historical precipitation measurement data to the current one.

2 RELATED WORKS

The related research presented in this study suggested the fundamental reason for constructing big data based on water resource instrumentation data and for using it as an analysis technique by deriving the current status and problems of water supply, with a focus on the management case of water resource data in Korea [16].

The data used in this study was based on the data collected by the Korea Water Resources Corporation, the

Smart Water Grid Research Center, and the big data management platform built for this study.

Figure 1 Cases of domestic water resources data collection

2.1 Current Status of Water Resources in Urban Areas in Korea

In Korea, it is essential to secure a water source with an alternative source technology due to the high cost of raw water supply in urban areas. In provincial island areas, the water supply rate is low at 56.6 percent, while the leakage rate is as high as 40 percent, which calls for improvements. Since these areas mainly use groundwater as a source of drinking water, it is hard to find fundamental countermeasures when there is little rainfall [17].

2.2 Status of Raw Water Use in Urban Areas in Korea

Major cities across the country purchase raw water from the Korea Water Resources Corporation (K-Water) and supply it to neighbouring areas. The purchasing cost of the raw water in Incheon is 126 won per 1 m^3, more than 10 times than Daejeon (12 won per 1 m^3), and 3 times higher than Seoul (49 won per 1 m^3). To lower the expensive cost of raw water in each supply region, it requires securing various water sources by expanding water intake stations, desalinating seawater, using groundwater and rainwater, reusing water, etc. However, it should also entail improvements to analyze consumers' consumption patterns in the fundamental water use and to utilize it as decision support.

2.3 Current Status of Water Supply in Urban Areas in Korea

Domestic tap water is supplied with branding customized to the characteristics of each region. However, its drinking rate is low due to a lack of trust and insufficient brand awareness. In addition, as there are few advanced water purification facilities to improve the quality of tap water by removing disinfection by-products and odour, each region is still expanding them. Yet, due to the lack of budget, it is expected to take about ten years in the future, so it is needed to improve the awareness of safe drinking water.

2.4 Flooding Cases Due to Domestic Precipitation

In 2020, Korea experienced the longest rainy season since 1973. In the summer from June 10 to August 16, four quasi-typhoons, "Rose", "Bobby" and "High Sun" landed in Korea sequentially. As a result, human and material losses simultaneously occurred. During that rainy season, the total precipitation in the country was 693.4 mm, twice as high as the average annual standard of 356.1 mm. The precipitation increased evenly across the country, marking 851.7 mm in the central region, 573.1 mm in the southern region, and 562.4 mm in Jeju Island.

2.5 Risk of Heavy Rainfall According to Precipitation in Each Region

The occurrence of localized heavy rain is increasing significantly due to climate change in Korea. The domestic rainfall hazard grades show that risk grades 1 to 2, which indicate a high risk from grades 1 to 10 in the heavy rain advisory standard, are centered on the southern coast, Jeju Island, and the metropolitan area. On the other hand, the eastern coast and inland regions show a level of 7 to 10, which is remarkably low. As such, the risk of high precipitation is concentrated in the metropolitan area and Gyeonggi province. Based on such past precipitation probabilities, this study intends to present a classification model to efficiently predict future precipitation by focusing on earlier cases.

2.6 Water Resource Data Management Policies in Foreign Countries

Water resource data management abroad is utilized across the smart city, which is becoming more complicated and interdependent with the direct introduction of big data into rivers, floodgates, and weather conditions. The development and application of a water resource system is currently under way. The most representative case would be the USA which operates the National Water Information System (NWIS) as an integrated system to store and retrieve water resource data. Also, through River Forecast Centers (RFC), the USA predicts water levels of all rivers across the country and, at the same time, makes river flood forecasts [18]. Moreover, the USA's National Oceanic and Atmospheric Administration (NOAA) daily collects over 3.5 billion weather data for utilization in public areas like government organizations.

Similarly, the UK's Foresight HSC (Horizon Scanning Centre) established a potential risk management project to support data-based decision-making to prepare for climate change and reduce flood damages considering the 20-fold increase in its annual flood damages. In Northeast Asia encompassing China, Mongolia, and Japan, Japan is geographically close to South Korea, and all of its territory consists of islands. Japan's Foundation of River & Basin Integrated Communications (FRICS) aims to rapidly provide information on river basins to disaster prevention agencies and the nationals. In the past, Hitachi Ltd.

proposed Intelligent Water Systems to utilize water resources wisely through smart cities.

2.7 Data Analysis and Pre-Processing Techniques in the Smart Water Grid Field

Data pre-processing is a crucial task in detecting significant information from massive data. The type of pre-processing procedure or technique affects the values and reliability of analysis results. Generally, analysis studies in the smart water grid field cover various themes from climate change forecasts, precipitation forecasts, and water scarcity forecasts and use many pre-processing techniques in the data analysis process [19, 20]. Currently, the most frequently used pre-processing technique is Data Handler. Data in a two-dimensional table form based on structured data utilizes Python-based Pandas and Numpy to set up data frames or arrays in a table form and to filter data by changing rows and columns. Also, in processing missing values, it filters all rows of a tuple where the value exists or replaces it with the average, and this pattern is frequently used in data mining techniques as well. However, such pre-processing methods are widely used for analysis studies in various fields, which means they are not independent, unique, and fit for the analysis target. Therefore, finding a suitable and realistic method for data pre-processing will increase the reliability of the analysis result, and in the case of digital data, the larger the data is, the more important the selection of pre-processing technique becomes.

3 PROPOSED METHOD

This study intended to derive an environment design to use big data analysis of water resources and precipitation instrumentation data. Accordingly, it established a server system, managed big data, and presented a classification model for instrumentation data.

3.1 Establishment of Big Data Operation Server for Instrumentation Data

A management platform for a big data environment is necessary because water resource and precipitation data has large volumes as collected in real time by sensors.

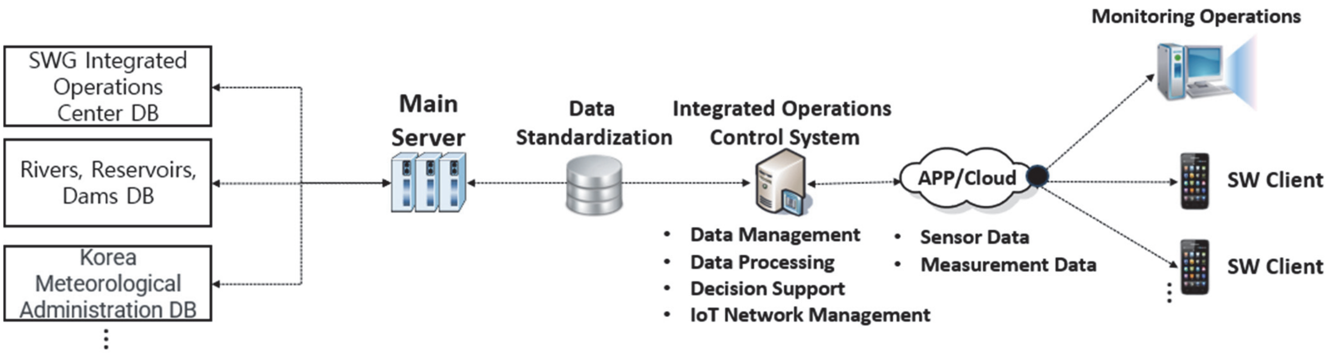

Figure 2 Big data management process of instrumentation data

This study defined a water resource-based instrumentation platform as data collection and storage technology, data integration and transmission technology, and data classification technology. The data collection and storage technology collected water resource data by linking the acquired instrumentation data and data from sensors installed in the region with the integrated DB of the related organizations. Then, it assigned a classification model according to data properties. Next, it established the data storage by collecting data required for service provision and big data analysis information from the relevant ministries. It also distinguished the data presentation type into water supply usage, water supply, water quality measurement, meteorological and precipitation, etc. according to service type in the classification model [5].

The technology played a role in securing the prediction information of precipitation. This study built a real-time streaming data delivery system of structured and unstructured data to collect various data in the IoT environment by supporting an open standard communication protocol that can accommodate various types of fragmented data and by utilizing the Meteorological Agency meteorological information DB and standard API to manage the instrumentation information of the smart water grid.

For water level data that lies at the core of this study, we utilized data collected in real-time from the water resource management operating system of the Yeongjong Island Demo Plant, the unit project of Smart Water Grid Research Center, and the precipitation data was collected from precipitation measuring sensors in the relevant regions. Although the meters measured precipitation data not smaller than 0.2 mm, in actual data classification, precipitation data not meaningful to risk factors was filtered out as missing values.

3.2 Structuring Data Warehouse to Utilize Predictive Analytics of Instrumentation Data

The operational procedure model of the data warehouse had a structure that can predict precipitation data by analyzing external data. In order to utilize precipitation data such as instrumentation data and past public data collected and held by the Smart Water Grid Research Center, it had to keep a space that can store geographic deformation information corresponding to existing regional data. For this purpose, the scale for processing qualitative data on water level overflow according to the past and present geographical requirements was set as follows:

The ETL model was used to store and refine the initial data of the past water resources and precipitation sensing data for data extraction, transformation, and loading, and the model operated on a disk-sharing basis.

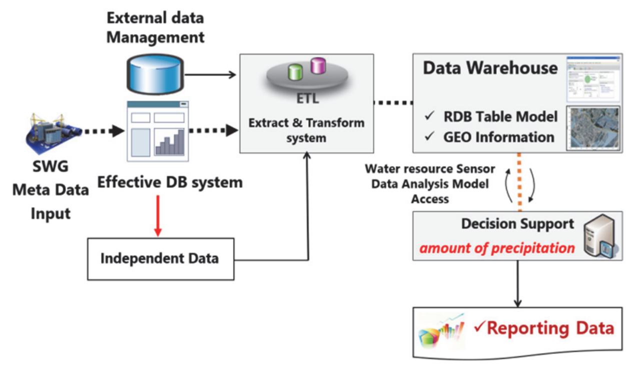

Figure 3 Building a DW optimized for big data and decision-making

3.3 Schema Structure Model of Instrumentation Data

The data warehouse schema used the structure obtained from previous studies. It consisted of a dimension table of location data applied to each category, that of weather data, that of water resource instrumentation and precipitation data, and that of time. It was a modeling of a fact table in a multidimensional space.

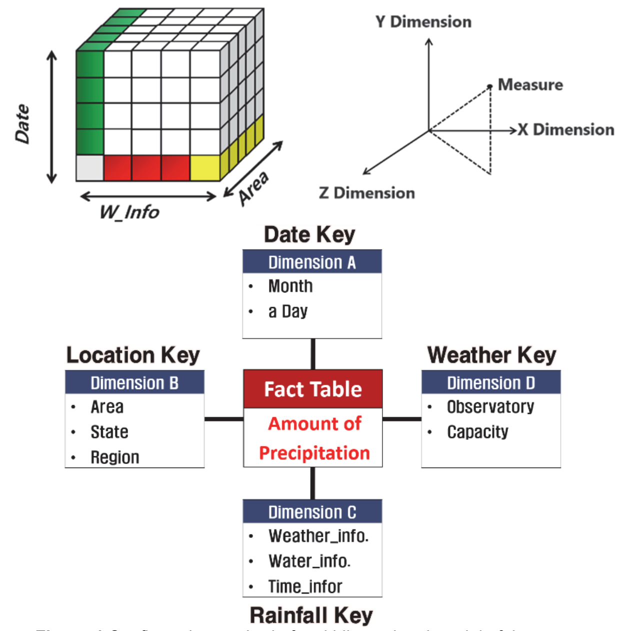

Figure 4 Configuration method of multidimensional model of the system

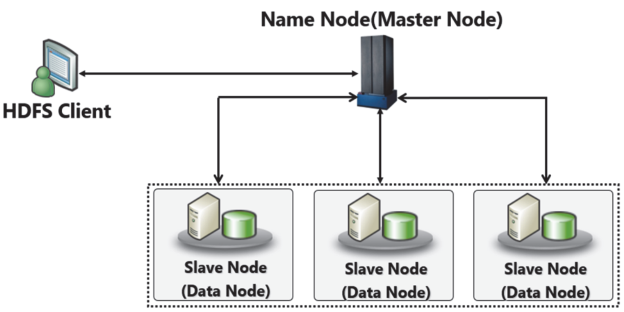

Figure 5 Application of HDFS

The operational management of Hadoop and HDFS is important in controlling the measured data in a big data environment. In addition, when water resources and precipitation instrumentation data are classified by type, the management of big data servers and networks can be regarded very important because most of them deal with structured data in statistics. It requires the HDFS, a distributed file system to improve the visualization of structured data and the stability of server operation.

3.4 Application of the Classification Model of Instrumentation Data

3.4.1 Collection Areas of Instrumentation Data

Yeongjong Island, Korea, has seen a sharp increase in water consumption due to growing floating and resident populations as the Incheon International Airport and new towns are developed [17]. Also, there have been voices that this area needs more thorough water management and safety by predicting the probability of precipitation due to its geographical characteristics as an island away from the inland. The reservoir applied to the Yeongjong Island Demo Plant Project, which was promoted by the Smart Water Grid Research Center, is divided into three sections: South, East, and North. This study presents a classification model based on the data measured at such southern, eastern, and northern reservoirs in Yeongjong Island, Incheon, and the precipitation data collected.

Figure 6 Field exploration of Yeongjong Island reservoirs in Incheon, South Korea, currently in operation

3.4.2 Clustering Classification Using Instrumentation Data

"Frequent patterns" means the patterns that occur often in a data set. That is, when applying them to instrumentation data, the common patterns were analyzed for the classification of frequent data. The instrumentation data on water resources consisted of structured data such as basic values, outliers, and missing values of annual water resource information. In order to extract and analyze important data from a vast amount of data, it was essential to divide it into normal data that showed a close periodic flow within the instrumentation history for the same period and abnormal data that showed deviant symptoms in a basic pattern. Therefore, it was necessary to create a transaction by dividing it into two groups. In this sense, this study introduced a method to construct a time series transaction based on the time and geographic location of the instrumentation data.

3.4.3 Classification of Data Collected from the Integrated Operation Center of Smart Water Grid Demo Plant

It collected more than 25 types of water resource data applied by the Smart Water Grid. The items that can be monitored by the Demo Plant Integrated System were divided into 9 information types such as flow rate, water quality, HMI, pressure, leak information, water source information, water balance, weather information, and consumer usage. Among them, it was possible to monitor the inflow and outflow of water, instantaneous flow, and accumulated flow in real time. In the case of water quality, it could monitor TOC, PH, Tubidity, EC, water temperature, TDS, etc. every hour. The following items are the types of data collected from the Smart Water Grid Integrated Center.

Table 1 Data items collected by the smart water grid

Data	Description
Search by Retarding Basin	Inflow Quantity, Stored Water Quantity, Suspended Water Level, Managed Water Level, Usable Water Quantity, Water Quality Grade
Search by Reservoir	Inflow Quantity, Stored Water Quantity, Usable Water Quantity, Water Quality Grade
Search by River	Flow Rate, Maintenance Flow Rate, Usable Water Quantity, Water Quality Grade
Search by Groundwater	Amount Available for Private Development, Usage Amount, Usable Water Quantity, Water Quality Grade
Search by Sea Water	Planned Capacity, Production Quantity, Water Quality Grade
Search by Purification Plant	Planned Water Supply Quantity, Waterworks Supply Quantity, Water Quality Grade
Search by Sewage Treatment Plant	Planned Amount, Treatment Amount, Usable Water Quantity, Water Quality Grade
Search by Available Water	Demand and Supply Quantity of Fresh, Agricultural, and Industrial Water by Available Water
Search by Rainfall	Rainfall of the Day
Occurrence of Alarm	Data at the time when a water shortage warning occurs that the demand for each water is bigger than the available water under the current conditions

In this study, it collected data from three reservoirs located in Yeongjong Island, Korea, as part of the Demo Plant Project. It applied only inflow quantity, stored water quantity, suspended water level, and usable water quantity, and manages the data by classifying the weather information into a multidimensional model. The data items of the precipitation analysis considering climate change were as follows.

Table 2 Precipitation analysis data considering climate change

Data	Description
Current Precipitation	The Accumulated Precipitation up to now and the past average data as of the present time.
Past Precipitation	The Displayed Data that visualizes past observation data as of the present time or Data of the Selected Date in a specific period in the form of graphs or tables.
Climate Change Scenario Analysis	The Future Precipitation Data with grids supplemented according to the latest administrative district map, User-selected Points, Administrative Districts, and Standard Watersheds in units of 1km*1km
Future Precipitation Forecasts	Neighborhood Forecasts of Meteorological Agency, Mid-term and Long-term Forecasts, and Past Average Data using Historical Precipitation Data, Future Precipitation Forecast Data using Climate Change Scenarios, Past Average Data, Future Precipitation according to the Korea Meteorological Administration Forecasts and Climate Change Scenarios
Precipitation Data Extraction	Precipitation Data of Coordinate Points, Administrative Districts, Standard Watershed Units, and Daily Units

3.5 Pre-Processing Technique of Water Resource Instrumentation Data

Although all the measured water resource data had been resolved to some extent through processing and classification, it was not yet perfect. As for the accumulated data, the data collected from the sensing device was classified based on the clustering model, and other data was organized according to changes in water inflow quantity and precipitation. The meaning of big data can be presented in various ways, but the ultimate purpose is to extract only some meaningful data from numerous data and utilize it. Thus, the classification model up to now removed the data of meaningless items and extracted only some meaningful data. Still, missing values, outliers, and invalid values existed due to the characteristics of water resource instrumentation data. To increase the accuracy of the analysis, we filtered these values as follows.

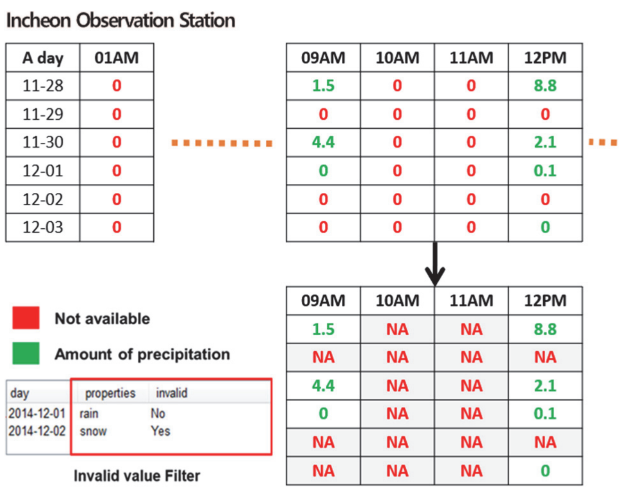

Figure 7 Pre-processing of invalid values and outliers in instrumentation data

In the first step, if the instrumentation data was precipitation, it performed processing of the missing values. It was to exclude the case where the precipitation measure did not affect the water resource data from the analysis category. In the second step, when the instrumentation data was precipitation, it performed the invalid value processing. The invalid value means all condensates, including liquids and solids, that reach the ground from the air for which precipitation cannot be measured, and this includes hail, fog, snow, sleet, and blizzard. It was divided into liquid and solid precipitation. Among them, hail and snow were removed since they did not significantly affect the water resource instrumentation data presented in this study. In the third step, when the instrumentation data was precipitation, it performed the outlier processing. The consideration of outliers due to climate change is important. It is necessary to analyze the degree of changes in precipitation compared with the same period last year. It is possible to compare with local water level data by detecting such outliers.

3.6 Analysis Process of Instrumentation Data

To analyze water resource instrumentation data, it is essential to select a local place. In addition, it needs to find out and classify the same generation patterns as an element in constructing a multidimensional model by specifying the division of past and current data. The data analysis model process proceeded as follows:

STEP 1. Select the same area, and calculate and classify its past information.

STEP 2. Classify the instrumentation data based on the same pattern by time, date, and region through clustering techniques, and derive the dimension and fact tables.

STEP 3. Normalize entity objects and create multidimensional cubes.

STEP 4. Derive and manage the predicted values of the instrumentation data scale through pattern data analysis using multi-dimensional cubes.

4 RESULTS AND DISCUSSION

This is based on the classification model of water resource instrumentation data presented by us. It is the result of analyzing water level overflow according to precipitation by applying one month of heavy rain in the Yeongjong Island Reservoir as a standard for the past two years. From the comparison of the water level among the precipitation data by applying the classification model of the instrumentation data based on the records of the past two years and the current same month, we obtained a result with a prediction accuracy of 80 percent or higher.

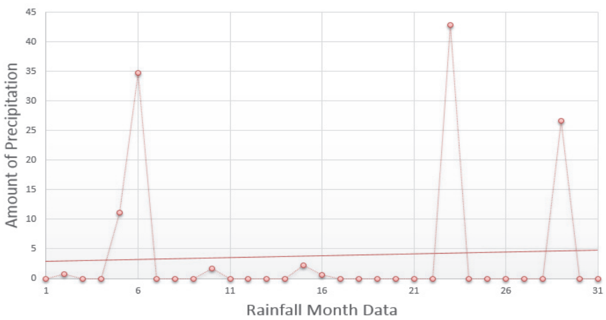

Figure 8 Sample A of historical precipitation data

Sample A and Sample B of this precipitation data are time-series graphs showing the collection of precipitation data from the same area for the past two years when frequent heavy rains occurred. What the two graphs had in common was that precipitation is high in both the first half and the second half of the month. The beginning of August was the end of the rainy season due to the climate characteristics of Korea, and the second half showed a measure of precipitation due to temperature changes before autumn. There may be differences in the two-year data due to the local natural environments and the influence of humidity, temperature, and clouds, but the pattern of precipitation can be said to be similar. The area is situated near the Incheon International Airport, and considering its location on the beach, it is characterized by frequent occurrences of fog and high humidity. The area also shows severe weather changes.

Some soils of the surrounding regions were seashore but reclaimed to increase the land area. While earlier studies analyzed flooding of precipitation by considering the influence of a drainage system in a region packed with buildings and structures, this study progressed in a very natural environment, which is quite different from a geographical standpoint.

It was data that did not apply outliers and invalid values unlike in the pre-processing technique of the study. Based on two types of past sample data, it classified the data into the pre-processing and clustering methods presented in this study and proceeded with the analysis process accordingly to obtain the results shown in Fig. 10.

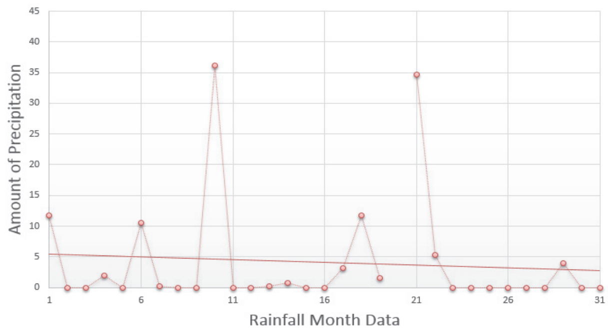

Figure 9 Sample B of historical precipitation data

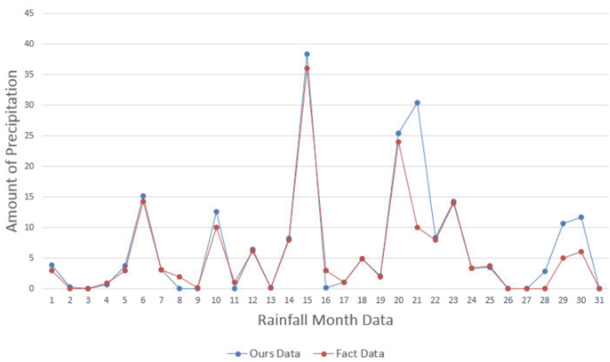

Figure 10 Matching result of average and predicted data for 2 years

It derived Sample A and B based on the month when heavy rains occurred in the same area for 2 years, respectively, and calculates the average value. In addition, it drew the prediction data by applying the classification model presented in this study based on the anticipated precipitation data for the next year. Fig. 10 shows the result of matching the historical data and the predicted data based on the fact data. From comparing the fact data, it was confirmed no items were significantly different from the fact data we predicted, although errors occurred in the second half.

The section in which the measured value is 0 in the time series graph shows where it did not rain or snow or where the precipitation was too low to cause flooding or natural damages. The reason for the frequent occurrences of rainfall lower than our expectations, which led to slight errors, is that the precipitation data that did not give natural influences was treated as missing values during the pre-processing.

The results of this study were drawn out based on the precipitation data received from the sensor and the water resource instrumentation data. It may cause some errors depending on the environment and climate change, but it was confirmed that the accuracy of predictive analysis can be enhanced depending on the amount of data and how the data is classified and analyzed. As a category of big data fundamental analysis technique, it can be applied as a model to obtain higher reliability of big data analysis by extracting meaningful data from huge data, filtering, and classifying it.

5 CONCLUSION

Focusing on the Smart Water Grid, this study proposed an effective pre-processing procedure to raise the reliability of big data analysis by utilizing water resource data and precipitation data. To secure the structured data and prepare for future climate change, it defined a classification model for precipitation data and proceeded with studies on methodologies to establish big data to predict precipitation information in a relevant region and studies on flexible methods to increase reliability. The expected effects of this study are that the pre-processing, which considered local characteristics and utilized the data secured from Smart Water Grid Research Center and precipitation data, can be reflected in an effective middle and long-term response plan for flooding. Also, as a challenging attempt to apply various data pre-processing techniques, it can represent an example of reducing rainfall damages in regions with similar environments in this study.

Since this study progressed on a small island centered on the Korean coast, it successfully raised the reliability of analysis results by performing pre-processing technique customized for the relevant environment. On the contrary, however, it has limitations in applying to other precipitation predictions according to water levels in different regions. Also, this study did not consider variable data such as diverse geographic conditions, ground components, densely populated areas, and whether there is a drainage treatment system. Thus, when geographical characteristics play a role in the relevant region, the reliability of this analysis result may drop. Still, this study result is expected to be an effective solution for small cities and islands vulnerable to precipitation change. To overcome the limitations of this study, future studies will consider the diversity of geographical features, secure data variables depending on different environmental factors, and focus on a prediction model for climate change that can be applied to various environments and geographical conditions.

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