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FLOOD CONGESTION SIMULATION AND PREDICTION USING IOT WIRELESS NETWORKS ON DYNAMIC STREETS ROUTES

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ABSTRACT

Floods are among the natural hazards that are the most common as well as devastating. The worrying numerous flood-related fatalities and economic losses incurred yearly globally call for enhanced flood prediction. Remarkably, the previous decade has presented great chances with a series of studious events investigating how wireless data from the internet of things (IoT) networks can enhance flood prediction. This paper backs by emphasizing the key approaches of flood congestion prediction and IoT sensor-based techniques for real-time flood observatory, flood prototyping, mapping, and prompt flood prediction systems comprising the water level estimation. With the exponential increment of data available and computational capability, simulation techniques for uncertainty approximation of flood prediction is presented. We present the development of IoT Flood Simulator system that process individual nodes as well as multiple nodes datasets of multiple-sources of roads conjunctions collected via IoT wireless sensor networks. The system also locates the predicted flood and shows warnings on real map of the study area.

Keywords: *Wireless sensor networks, Floods prediction, Dynamic streets routes, IoT Technology, Simulation.*

1. INTRODUCTION

The effects of disasters are adverse on several aspects of life, which include the environment, the economy as well as the well-being of people as it affects the delivery of essential services like healthcare, transportation, and communication among others. These negative effects entail the destruction of the property causing losses in addition to the loss of lives. One of the most common types of disasters is floods. Statistics from the World Meteorological Organization (WMO) ranks floods as the third biggest disaster that affects various parts of the world [1]. According to the United Nations Office for Disaster Risk Reduction (UNISDR), a number of natural disasters inclusive of floods have resulted in the destruction of property worth trillions of US dollars as well as the loss of lives of approximately 600,000 people in the last 20 years [2]. To make matters worse, approximately 60% of the cities around the world are expected to be prone to flooding. In the next three decades, which will be attributed to the changes in the climate that would lead to the rise of the sea levels as pointed out by the research carried out by the Institute of Environmental Studies [3].

Floods are most of the most devastating kinds of weather-associated disasters faced currently. They can be caused by heavy rainfall or by the failure of fabricated structures like dams. Flood poses extreme danger to vehicles crossing roads even with minimum speed that cause traffic congestions and other disturbances. The danger increases with heavy traffic roads in crowded cities. The rapid development causes flash floods that inflict extra problems for early forecasting in comparison to riverine floods. Structural actions implemented to decrease the effect of these occurrences comprising in comparison to erecting the physical components intended to improve totally drainage systems' resilience like levees as well as detention ponds.

A core characteristic of this paper is the ability to perform accurate and timely flood congestion prediction. Techniques for flood congestion predicting require a continuous enhancement, majorly in the present context of progressive changes in climate change and urbanization that result in an incremented susceptibility to floods observed in diverse locations globally. This investigation offers a chance to update scholars on present developments in flood monitoring, as well as the use of technology in review to map flood occurrences. The inspiration behind this research is to highlight prevailing solutions and adapt them to enhance the management of coastal lagoons that cause flood risks to inhabitants of cities. This study postulates a systematic review of the available literature concentrating on the application of IoT founded wireless networks in flood monitoring, prediction, and mapping for the road network. A key influence of this article is that a comprehensive survey offers employment of IoT wireless networks on a real street flood street dynamic routs monitoring, mapping, and prediction. Mainly this research study focuses on the development of a flood simulator system for roads routes conjunctions. The scope coverage is of the computer vision equipment and IoT sensors combined techniques for the road networks and other regions in Kuwait cities.

2. BACKGROUND STUDY

The flooding events are improbable to change; nevertheless, its effects on society can be decreased. Effective prediction as well as early systems of warning can aid in the mitigation of floods' effects. The last decade had been a crucial period in association with flooding around the globe due to many reasons as per National Geography [4]. Some of the most widespread, costly, and damaging floods have happened in wealthy, developed countries. Flooding in less developed countries has seemed to be incremented as well as serious. Those floods have become growingly related to climate change as per the general and media view, which has been of a rising flood and storm frequency, apparently arising from global warming [5].

Xie et. al. [6] mentions the wireless sensor network equipment with a capacity of flash flood occurrence mapping in urban centers. The improved wireless sensor network was designed to deal with flooding challenges in China's low-lying regions by Zhuang et. al. [7]. The flood detection sensors, Xbee transceivers, and microcontrollers embedded in the node that monitors flood happenings. The system senses floods happening and transmits a notification via Public Switched Telephone Network (PSTN) to a management station. In associated work, Islam et al. [8] made a wireless network system to regulate floods in Bangladesh. The transducers for water level, microcontrollers were embedded within the sensor node plus Ethernet component for wireless communication. Thus, monitoring in real-time was gained. The research done by Pati et al. [9] mentioned the social susceptibility of the flood-prone urban centers in the Philippines was also obtained by the use of proxy indices. The flash flood prediction is very significant for every community ought to embrace specifically in the coastal and riverbank. The paper postulated by De Castro et al. [10] to advance technology on the warning of floods by the use of SMS with developed information warning grounded on forecasting algorithm concerning rising water level as well as water speed.

To offer precise data analysis that will collect for a probable flood, Kitagami et al. [11] recognized an efficient IoT application for disaster forecasts. To analyze the technique, they designed a model system also conducted a field attempt in the province of Quang Nam, Vietnam. Due to evaluation, the suggested technique can decrease the load of the network for flooding monitor but also provide the flood warning at a precise time. Some flood threat evaluation applies a statistical prototyping algorithm that plays a significant role in the sensor networks. Likewise, Basha and Rus [12] suggested a network sensor with a statistical prototyping algorithm for river flood forecasts. It is established on the regression prototype, which implements considerably better than present hydrology study versions at hourly forecasts for modeling and substantiation motives, was tested by use of seven years of data from Oklahoma's Blue River. Kayte et al. [13] developed the application of the Raspberry Pi sensor in a project to monitor the water level in a dam by use of the advanced concept of IoT fitted in it to provide a similar purpose automatically. That is also to transmit the status to the Raspberry Pi as well as to upload status on the website. Flood threat analysis offers precise data for online flood prediction. The latest researches apply wireless sensor equipment like water pressure, water level, and rainfall gauge distinctively.

2.1 IoT and Disaster Management

Currently, the concept of IoT has been used widely in a number of study areas comprising disaster management. Kevin Aston, who coined the term IoT in 1999 [14], also defined this concept as exceptionally distinguishable linked objects by the use of radio-frequency identification (RFID) technology. The definition became vivid in 2009 by the International Telecommunication Union (ITU). They defined it as a worldwide infrastructure for the information culture that facilitates development services by interlinking both physically and virtually things established on prevailing and developing interoperable information as well as communication technologies [1]. RFID is a basic technology for IoT that permits microchip to handover the identification information via wireless communication. The RFID attached object can be monitored, identified, and tracked through the RFID reader [15]. An alternative technology for IoT is the wireless sensor network that is employed to interlink intelligent sensors. The WSN usages involve monitoring the environment, healthcare, industry, and traffic. These two technologies are majorly back the evolvement of IoT. The interlinked things and objects not only access the information from the environment but also interact with the physical world by the use of the internet standard offered services in information transmission, applications, and communications. The objects can be RFID tags, sensors, tablets, laptops, smartphones, and embedded systems with restricted capacities but with the ability to link to a wired or wireless network with or without IP address.

At present, IoT has been employed in a number of areas comprising safety, healthcare, smart city, manufacturing, inventory control, asset tracking, disaster management, and environment control. In disaster management, it offers benefits through monitoring, controlling, sensing, and tracking the environment by applying real-time data. IoT equipment can also aid in the provision of a simple communication medium during a disaster. The outcomes from case studies show that the integrated information system established is significant as well as effective for intricate responsibilities in environmental monitoring and management [16].

The use of IoT technologies is clear in undertaking the difficulty of monitoring the flood especially by the use of rain gauges. IoT offers an interface for data streaming management not only in real-time but also at the back end offer data scrutiny plus visualization. In this technique, the data gathered will be continuously transferred through the internet communication framework [17] to the software modules. When IoT is applied to flood sensing occurrences in real-time can be termed as Internet of Floods [18]. The software modules have developed to calculate the stream flow and to compute the spatial circulation of the flood threats, each regulated watershed. For instance, long-range (LoRa) is a spread spectrum method for modulation consequent of chirp spread spectrum technology. Semtech Company's LoRa wireless RFID and devices are of long-range with low power wireless framework for IoT networks globally [19]. These devices are regarded as smart devices in a wide range of application fields.

2.2 Approaches to Flood Prediction

The express development is manifested in remote sensing technologies, like satellite imagery, as well as in synthetic aperture radar satellite (SAR), which takes care of higher spatiotemporal resolution [20] of data with a wider coverage area, even at sparsely-data areas. Integrated with the enhancement in precision, the development in streaming services of proximate real-time is only received, as there are many usage opportunities in the society. National security and environmental monitoring are good examples. Such disasters can include landslide, forest fire, earthquake, and volcanic eruption or flood occurrences as discussed by Altaweel [20]. Remote detection can be grouped into two main processes: gathering and processing the data and analyzing it by use of electromagnetic (EM) sensors. EM waves are sensed [21], timed, and measured. Various kinds of EM waves can be gathered, each having particular capabilities or properties. Current researches in nowadays casting, not only the method of forecasting in the very near future will occur, but also data incorporation will take place. For instance, Poletti et al. [22] integrate radar rainfall monitors with numerical prototypes to forecast the flash floods in almost real-time of two to eight hours. This information can be fed into social media networks and media houses to alert the public.

The smart cameras can provide massive added value for assessing the flood effect on society in high detail. Because of innovations in technology, like intelligent image processing and pattern recognition algorithms using progressively superior microprocessors, smart cameras can do functions such as identify an object plus its motion, object measurement, vehicle license plates, face recognition and human gestures [23][24]. Technology also presented by smart sea buoys that can sense tidal waves, it senses fluvial floods. Furthermore, they can be applied for tidal wave detection. It can also measure water characteristics (flow velocity, water depth), water quality, and water temperature. Smart buoys transmit processed information to the meteorological servers and can predict the flood about a few hours before [25]. Currently, IoT established a level of water monitoring systems that measure water level in real-time with the application mounted sensors (e.g., pressure sensors, ultrasonic sensors, water sensors); it is being used more frequently in rain [26][27].

3. THE NEED OF MODELLING STREETS FLOODS IN KUWAIT

The objective of flood congestion prediction is to issue early warnings about the level of water or large discharge sufficiency which endangers the safety of life, structures, and flood plain events. Because of this, an early warning of this kind enables authorities to adopt a series of measures to contain the hostile effects of the flood. Kuwait as a country that did not experience flood disaster till last year due to unexpected global climate change recorded many losses in the country. Kuwait extends in a desert region that makes it vary in its climate. Past records of Kuwait international airport station report wide yearly range of temperatures between 6.4 to 10.6oC in winter seasons and during summer seasons ranged between 43.0 to 48.6oC. Occasionally, temperature exceed this range that harsh environmental conditions in Kuwait. However, rainfalls in Kuwait unexpectedly affected by weather-related hazards. Kuwait international airport station recorded the annual precipitation of 1979 was 244.8 mm while in 1964 was 32.2 mm [28]. Based on that, the significant factor of Kuwait ecosystem never shows a homogeneous curve to understand climate conditions. And therefore, it is not clear to researchers and decision-makers how the infrastructure of designing roads and water drainage networks should be.

In this case, in Kuwait City, forecasting by the use of data-driven hydrological models is appropriate like machine learning. It is deliberated that deterministic and reductionist prototypes are not suitable for real-time prediction due to the intrinsic improbability that describes the river catchment dynamics and model over-parameterization issues. The benefits of extra, effective parameterized data established mechanistic prototypes, recognized, and approximated employing statistical techniques are discoursed. Because of that, the machine learning prediction methods prototype, flood historical occurrence records, and real-time cumulative data of other detecting smart devices for numerous return periods are often applied [29]. Furthermore, weather radar observations with high-resolution offer reliable datasets in comparison to rain gauges [30]. Hence, building a forecasting prototype established on the radar rainfall dataset was reported to give a higher precision in common. In this study, the IoT simulation system connected to Matlab capabilities [31] is appropriate.

4. RESEARCH METHODOLOGY AND THE PROPOSED FLOOD PREDICTION MODEL

4.1 Flood Simulation

Iot Technologies play the major role in our approach. We build an IoT Flood Simulator system that uses Matlab as a backend simulator based on data received from several locations in Kuwait's main roads network. The system is based on three basic layers. The first layer is acquiring initial data from each location via IoT wireless communication system. Each IoT unit is considered as a node located at roads conjunction with high impact flood. Data such as rainfall measured with the flow directions either received from the nodes or providing to other nodes. The data will be collected in a control unit and saved in the form of Excel files to be used later. The second layer is the simulation process itself. Once data are fed into the system, the simulation process starts by linking to Matlab in the background. Results are then saved and returned back to the system for further analysis. The third layer concerns the analysis part and transmitting warnings to other IoT registered in the network. The overall recommended results will be highlighted in the map of Kuwait that must be activated in advanced in the IoT Flood Simulation System.

4.2 Structuring the Model and Preliminary Setting

A general process flow diagram that defines the model structure is illustrated in Figure 1 and Table 1. Figure 1(b) shows satellite view of Kuwait City to Ahmadi City. The major roads are shown in Figure 1(a) representing the most significant and high spotted flood provider nodes and the flooded nodes. Those main roads are considered the backbone of the country serving more than 90% of the residential areas. All nodes are linked to each other in the structure. The various sensor setups would be located in the 62 locations with the IoT components, referred to as Nodes, for the purposes of collecting and transmitting data. Mainly in the historical records, there are seven clusters (we mark them cluster A to cluster H) that are reported as flooded with disaster impact on life and cause deadly closure to streets and disconnect residential areas. The flooded nodes marked by the letter 'F' followed by its location area. The north side nodes are recognized by letter 'N' and the southern side nodes recognized by letter 'S', followed by a serial number hence nodes names such as "FS20" or "FN21". In the southern area, cluster A considered the most tragic. Most flash flood congregates in this area due to its immediate adjacent clusters B and C. Two flooded nodes impacts from this vicinity that is nodes FS20 and FS21 as shown in Figure 2 and Table 1.

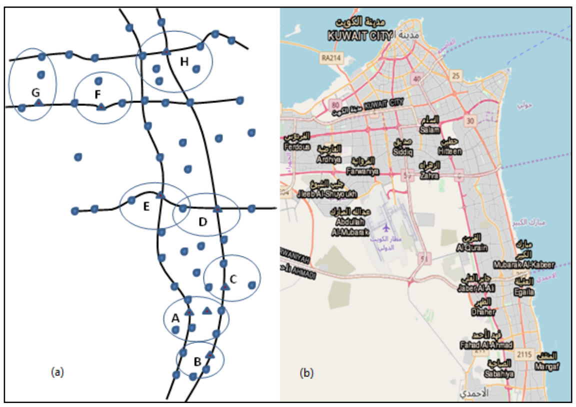

Figure 1: (a) Main Roads view. (b) Satellite view of Kuwait City.

Table 1: Clusters and nodes simulated in Figure 2.

Provider Node (High Spotted)	●
Flooded Node	▲
Cluster	Node
A	FS20 , FS21
B	FS27
C	FS17
D	FS6
E	FS4
F	FN19
G	FN17
H	FN7

After the preliminary setting presented in Figure 1, the transceiver node should be placed at the most spotted Nodes. Figure 2, delineates the structure of the design of the Remote Sensor Network that would utilize remote detecting to discover that precise and solid information almost floods are recorded and transmitted from nodes to the controller. The ultrasonic sensor measures the time from the dispersion of the ultrasonic pulse to the reception and detects water levels with great accuracy. Whereas the water flow sensor is used to measure the water flow rate that passes per unit time.

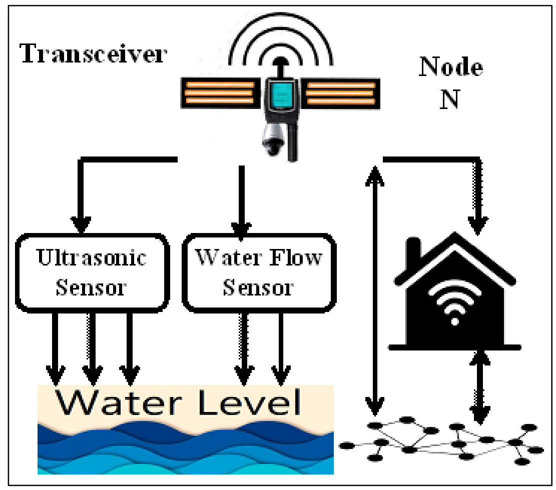

Figure 2: The Transceiver Node and IoT of the datasets.

The various sensor nodes are tasked with capturing the information about the floods which include the velocity or the flow of the water, the level of the water, the precipitation and speed among others. The smart control system, on the other hand, is tasked with the responsibility of processing the collected data by the various sensor devices at the same time transmitting the said data to other nodes and the controller node. During heavy rainfall, the precipitation sensor on its part would be employed in measuring the precipitation that would be presented.

4.3 Data Preparation

Data collected from IoT and Kuwait weather forecast department for all nodes in main roads network. Each node forecasts a reading either in an hour or daily levels of water. A provider node will then be simulated in the model, each with output variable that provide multi-output to adjacent nodes. The parameters are calibrated by the use of one of the numerous learning algorithms in Matlab, applying a commonly employed model that makes facilitation in comparison with prevailing researches [32][33].

Usually, for the simulated model, partitioning of datasets is divided into subsets of three: training, validation, and testing. The subset training is applied to calibrate the weights and biases, while validation is applied to terminate training. Then the subset testing is employed to assess the performance of the model. The amount of rainfall would be labeled of +1 and -1 levels hence ensuring that the data that has been collected in the process is reliable. In this study, the dataset is then partitioned into training, then validation and finally testing clusters separately. A general process flow diagram that defines the model structure presented in Figure 3.

The simulation process used for this study that is the most commonly applied in Matlab Simulator for flood prediction. It comprises an input node, adjacent nodes, and output; each node is dynamically linked to other node in the adjacent array. To add on the function of predicting the likelihood of floods and the direction of the floods to adjacent nodes, the system would also provide a history of data of the various nodes that have taken place in the past to be presented in the model for the simulation process.

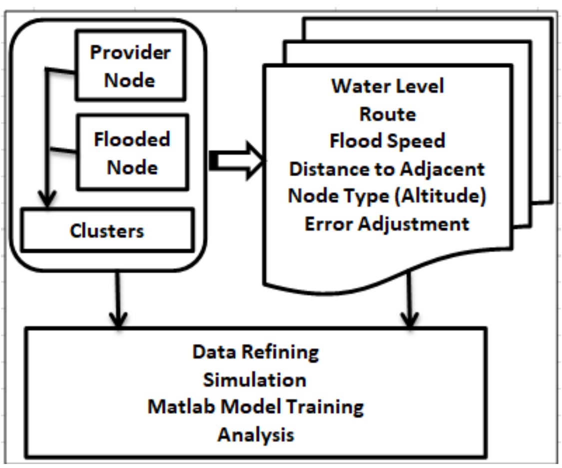

Figure 3: Model Structure and nodes partitioning of the datasets.

4.4 Flood Routing at Roads Connections as Nodes

The dataset sources are water level and rainfall, measured by IoT supportive remote detecting technologies like satellites, radars, and multi-sensor systems. Data collected represent multi-dimensional data sets. Furthermore, the simulation process comprises all connected nodes in the model. This study applies the simulation processes to obtain the establishment of the flood-forecasting model [34]. Choosing the indexes provided by the IoT Flood Simulator System can show the effect aspects such as disaster causing factors for each node fed to it as well as the affected nodes and highlighted in the map in the simulator system. The process starts with the determination of the network structure, the number of nodes in each sector, and the transfer function and tackle the training algorithm as per the input data. Training continues with modifying the weights and error adjustment thresholds as per diverse needs and offer the data to validate and test it.

Providing the data test to the simulator trained and forecast results will be achieved. In comparison to the preferred output, the test precision is obtained. The flood prediction evaluation outputs are then tested based on error convergence to the most appropriate threshold. Figure 4 shows the display of historical data from the IoT Wireless Sensor Network for each node N to the base cluster. As such, both past and future conditions of the flooded node in the respective areas would be presented accurately by the system. There are various advantages that are associated with the proposed Wireless Sensor Network with reference to its accessibility in that one is able to effectively access the system through http protocol in its web browser which would be presented to all other nodes in and out the clusters and to other stakeholders to be able to access the information from the system. In addition to the web application, there would be also the Wireless Application Protocol (WAP) version of the system employed for early-warning [35][36]. The Wireless Sensor Network processes the information that has been collected and measured by the various wireless sensor nodes and transmits the processed information through Web services.

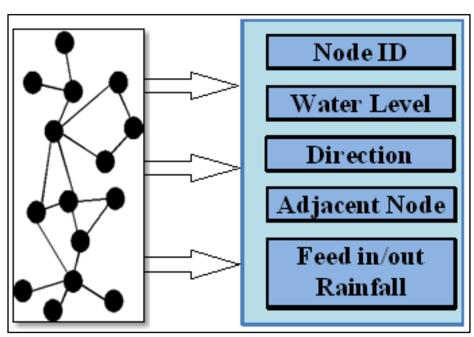

Figure 4: Dynamic road connections network of the datasets.

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5. RESULTS AND DISCUSSIONS

The flood routing street process can be computed by either a one-dimensional prototype or a two-dimensional prototype; if a general empirical equation is applied, there are simplified calculations as well as an increased computation speed [37] [38]. In this research, all nodes are considered as either providers to other nodes or receivers from other surrounding nodes. The series of nodes represented in the dynamic connection in each cluster area are illustrated in the set of FNi where {Ni | i = 1, 2, … ,n}. This dynamic orchestration makes each node a transceiver i.e. a flooded or non-flooded.

The IoT system for flood monitoring is made of multisensory network devices including an ultrasonic sensor for detecting the level and distance by signal transmission, and then it computes the time between sending and receiving the signals for the level of water monitoring. The general scheme application of the suggested flood observation is presented. The amount of flow received at N node is given by NT as in Equation (1).

$$NT_{(Flow)} = N * \Delta S \qquad (1)$$

where: ΔS is the change in flow speed for each node N. The provider nodes in nodes set FN is given in Equation (2).

$$FN_{Prov} = PT_{Flow} * \Delta T_N \qquad (2)$$

where P is the prediction in each cluster as shown in Table 1. The difference in time is represented in ΔT for each node N. The prediction of each cluster fed by all adjacent nodes *Pcluster* is computed as the product of the summation of all flow amounts received from the provider nodes multiplied by the change in time ΔT as shown in Equation (3).

$$P_{cluster} = (\sum_n nProv) * \Delta T_{\underset{n}{Prov}} \qquad (3)$$

where nProv is the total received amount from all providing nodes. The IoT sensors data transmitted will be computed in the summation over n nodes. The time T needed for the node N to have a flow is crucial; only and if N has received a sufficient amount of water. This value is indicated by the received water level value from the provider node mentioned in Figure 4 hence nodes that contribute to a flooded node is treated as provider node. In this case, computing time depends on real rain change and to other flooding nodes (areas) or water drainage from the surrounding nodes; thus, dynamic routes offer dynamic nodes representation.

The suggested model architectures are executed by the use of Simulink tools of the model. The suggested datasets were split for training and testing. Figure 5 illustrates the comparisons between elevation differences and flood percentage of datasets recorded from the real flood in nodes shown previously in Figure 1 for the suggested model. To strengthen the model, extra factors are added such as the altitude (elevation) of nodes of streets. This is due to road structure in residential areas that provide flash floods from drainages located along the routes connected with the main roads. The number of the most spotted nodes in the study marked n1 to n10 representing the north parts of Kuwait and for the southern areas nodes were marked s1 to s16. The actual flood "FN" or "FS", in capital letters, nodes are also scaled showing provider nodes and also form the main clusters.

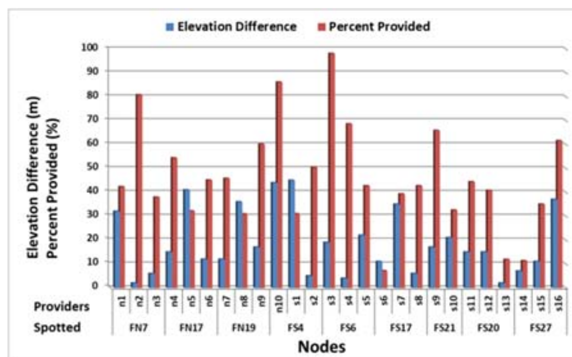

Figure 5: Datasets recorded of nodes and flood percentage provide.

It is known that the topography of Kuwait is close to the sea level, and therefore its land elevations are almost flat. Therefore, elevation differences measured in meters. It does not exceed a hundred meters above sea level in most areas. The scores manifest that offering more data did not significantly enhance the precision of an entirely linked prototype. Nevertheless, it can be manifested that the selection of the model has significant impacts on the total testing performance of the model. The predicted flood where the level of water has been tenaciously rose to bypass the intermediate alert level above 35cm in testing the model is a significant threshold. Whereas the levels of water on the actual test location at node FS17 (Shouaiba Industrial Area) is clearly noticeable.

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The y-axis in Figure 6 represents the flash flood provided in a 1-hour time span for which water level has risen above the ground level guard, signified by zero, for about 4h time duration.

The real measurements and values that predicted street flood per node are offered in Figure 6. After simulation, shared outcomes propose that when the stage does not illustrate changes dramatically, the model is successful to anticipate the next measurements. However, there are seeming fluctuations, yet it provides the same forecasts. It should be noted that even though the predictions appeared rarely illustrate a precise match with real measurements; they do not have large numeric variances.

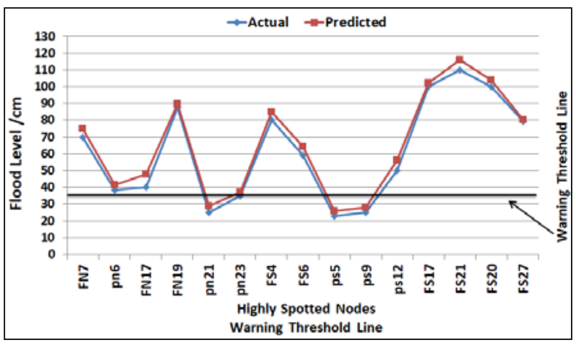

Figure 6: Simulation results: actual datasets and predicted results.

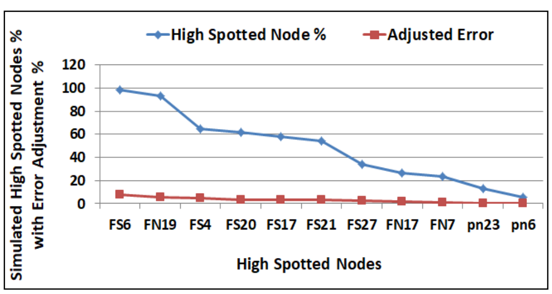

Figure 7: Simulation summary. High spotted Nodes with error adjustment.

Since the simulation reported results that are converging in most percentages to the similar measurements and predictions the model made, it can be mentioned that the total performance with the suggested dispersed technique is acceptable. Figure 7 illustrates the simulation results with error adjustment of high spotted nodes. This introduces the idea of applying a momentum for the simulation process. Because clusters represent variable nodes, sigmoid functions were added as well and adjusted to refine the data received from different clusters. The alterations with error-correcting the model expect affinities that are close to the veritable supports in both preparing and validation the datasets.

5.1 Error Corrections and Adjustment

Matlab uses cyclic redundancy check (CRC) coding technique for detecting errors where as in this research the structure of nodes collected by the IoT transceiver and recorded in the datasets are used as the input variables. In our IoT Flood Simulator, the scalar for computing the error adjustment is done by modifying the rate of change for the net momentum to each node. The output of each provider node is then multiplied by a momentum of real value m bounded between two and three. The log function of m to the base 10 is then multiplied by all recorded vectors in the dataset to adjust the error looking for a global minimum rather than a local minimum.

In the various network of roads that are interconnected in a given area, the Wireless Sensor Network would be able to accurately predict the conditions that would be present after the information has been collected, transmitted and processed. In this case, the different areas that have the sensor nodes would get the true picture of what would happen later. As a result, the direction in which the floods would be expected to occur would be reliably predicted from the simulated data that has been presented to the main server for purposes of prediction. In this sense, there would be warnings that would be issued in the areas that the data would show that they have a high risk of flooding which will be sent as a notification to the respective areas and stakeholders as illustrated in Figure 8.

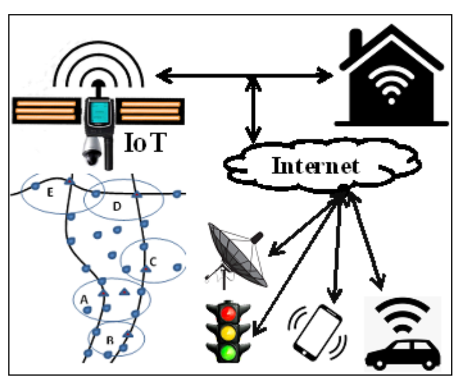

Figure 8: Simulation results as a Warning System.

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However, after activating the map as in Figure 9, results will also highlights the predicted nodes. This would ensure that appropriate measures are taken to manage the expected floods to avoid loss of lives and destruction of property. Finally, the obtained data can remotely store for likely extra explanation such as using e-mail alarms and SMS activated with aim of notifying about the probable danger.

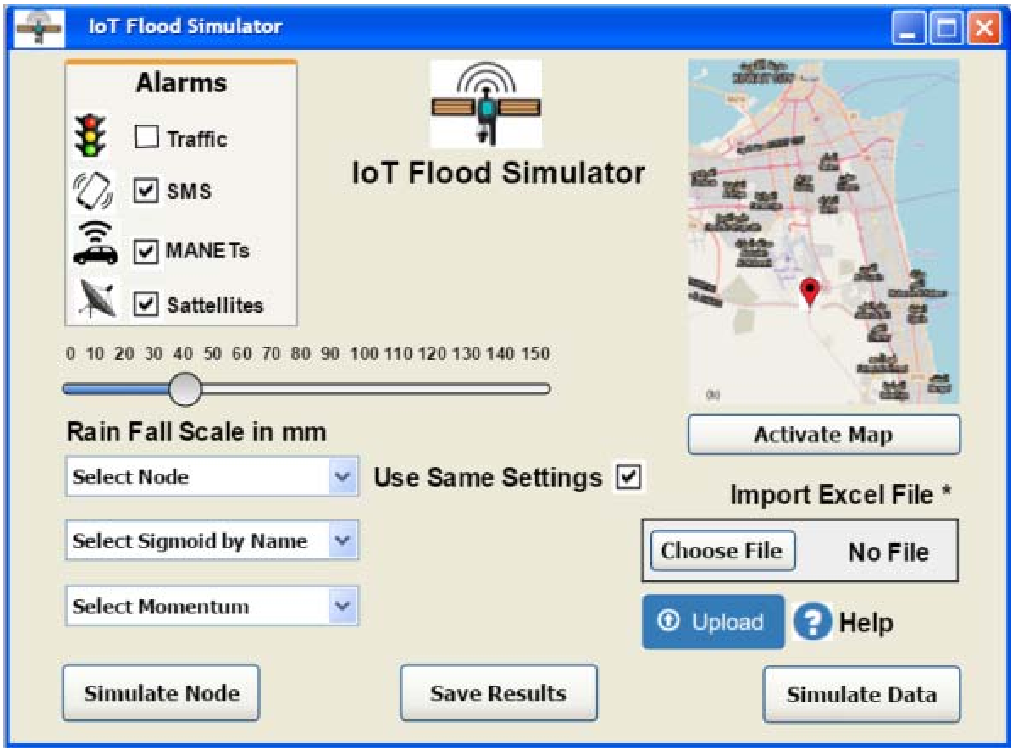

Figure 9: The Simulator User Interface system.

5.2 The Simulator System Interface

The user interface can do both manual and auto simulation for predictions. The user can setup the simulator to simulate a node by selecting the node from the map after activating it. Alarms and the rain fall scale is another option together with the dropdown lists that provide specific feeds to the simulator. There is another important functionality added to use the same setting when using the simulator in its auto mode. Usually the IoT transceivers provide the actual reading saved in files, the simulator can also accept those files in .csv or in excel formats and do the simulation process. The results will then highlight on the activated map and messages are then send to the selected alarms.

6. CONCLUSION

The flood simulator system based on wireless sensor network that has been proposed ensures that accurate information about floods in a given area would be presented in time as well as pointing accurately to the direction or the location where the risk is expected. In this study, an autonomous flood forecasting system based on IoT technology has been presented. The wireless technology selection and sensor node with the past shown structure proved how efficient is to gain energy performance appropriate for IoT devices. Furthermore, we demonstrated the expansion of the suggested systems made with multi-sensor to simulate, predict and monitor numerous parameters. The potential of data processing at advanced levels makes the system scalable to numerous devices, depending on the IoT gateway. Models suggested in this research with single and multi-node inputs can be used to offer more improved predicting results on operational information systems along with predictions of complex hydrological dynamic routing models. Presented outcomes illustrate that the simulation of flood prediction method used for Kuwait City's streets is expected very near to the real measurements.

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