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# Traffic flow prediction using orthogonal arrays and Takagi-Sugeno neural fuzzy models

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***Abstract* — Takagi-Sugeno neural fuzzy models (TS-models) have commonly been applied in the development of traffic flow predictors based on traffic flow data captured by the on-road sensors installed along a freeway. However, using all captured traffic flow data is ineffective for the TS-models for traffic flow predictions. Therefore, an appropriate on-road sensor configuration consisting of significant sensors is essential to develop an accurate TS-model for traffic flow forecasting. Although the trial and error method is usually used to determine the appropriate on-road sensor configuration, it is time-consuming and ineffective in trialing all individual configurations. In this paper, a systematic and effective experimental design method involving orthogonal arrays is used to determine appropriate on-road sensor configurations for TS-models. A case study was conducted based on the development of TS-models using traffic flow data captured by on-road sensors installed on a Western Australia freeway. Results show that an appropriate on-road sensor configuration for the TS-model can be developed in a reasonable amount of time when an orthogonal array is used. Also, the developed TS-model can generate accurate traffic flow forecasting.**

***Index Terms*— Sensor configuration, traffic flow forecasting, Takagi-Sugeno neural fuzzy models, orthogonal array, experimental design methods**

## I. Introduction

In modern cities, traffic flow predictors are essential for traffic control centers in order to reduce traffic congestion and improve mobility of traffic flow [11, 13]. These have a functional relationship which maps the past traffic flow conditions captured by on-road sensors to the future traffic flow at a particular location of interest. They are usually developed to forecast the traffic flow conditions on a horizon only a few minutes ahead of the current time, in order to provide proactive dynamic traffic control actions [13].

Typically, conventional statistical methods such as filtering techniques [7, 10], autoregressive methods [14], and k-nearest-neighbor approaches [1] have been used to develop those traffic flow predictors. More recently, the universal estimator, namely the Takagi-Sugeno neural fuzzy model, (TS-model) [2, 9, 15], has been applied for traffic flow forecasting, whereby better forecasting results can be obtained than by those approaches using statistical methods. As the TS-models are more capable of addressing the strongly non-linear characteristics of traffic flow [6, 12] than the conventional statistical methods, they can generally achieve better traffic flow forecasting.

Prior to developing the TS-models for traffic flow predictions, it is necessary to determine an appropriate on-road sensor configuration [4, 16] which illustrates the appropriate locations for the installation of on-road sensors and the appropriate number of on-road sensors needed to capture traffic flow data. However, the trial and error method is generally used for on-road sensor configuration design. A systematic way of determining appropriate on-road sensor configuration has not yet been resolved. In fact, the on-road sensor configuration significantly affects the forecasting accuracy of the TS-model. When the useful traffic flow data captured by the significant on-road sensors are not taken into account when developing the TS-model, the resulting TS-model is under-learnt by the insignificant traffic flow patterns. It can address only partial traffic flow patterns for forecasting purposes. When too much useless traffic flow data captured by insignificant on-road sensors are used, the TS-model can only address spurious patterns for traffic flow forecasting. Therefore, misleading traffic flow forecasting could be generated by the TS-model.

To obtain an appropriate on-road senor configuration, full factorial design can be used by switching the on-road sensors on and off using all the combinations. However, it is impractical and time-consuming to trial all on-road sensor configurations, as it may involve a large amount of experimental time. As an example, if there were only 20 sensors installed on the freeway, more than one million (or $2^{20}$) on-road sensor configurations would need to be trialed.

Therefore, a systematic and effective methodology based on the experimental design approach [5, 8] is proposed in this paper, in order to determine the appropriate on-road sensor configuration. The orthogonal array commonly used in experimental design is used to conduct systematic trials on on-road sensor configurations. It is used to study the effects on all on-road sensors with a small number of trials. It then estimates the main effects of the on-road sensors in order to optimize a given performance measure, which is typically the difference between the actual data and the responses of the traffic flow predictor. It is intended to develop a highly accurate and timely traffic flow predictor. A case study is conducted using traffic flow data captured by the on-road sensors installed on a Western Australia freeway. The advantages of using the orthogonal array is indicated in the developed TS-model: (a) high accuracy for traffic flow forecasting can be generated by the developed TS-model; and (b) the development of the TS-model requires only a reasonable amount of time.

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The rest of the paper is organized as follows: Section 3 discusses the general on-road sensor configuration of the TS-models for traffic flow forecasting. Section 4 elaborates on the use of orthogonal array in determining appropriate on-road sensor configuration for developing TS-models. Simulation results for traffic flow forecasting are presented. Finally, a conclusion and suggestion for future research are presented.

## II. EXPERIMENTAL DESIGN USING ORTHOGONAL ARRAYS

This section presents the mechanism of using orthogonal arrays for experimental design. When engineers design a system, their first step is usually to consider which components are necessary for the system. To do this, they could conduct experiments with respect to the components using the 'full factorial' approach, whereby each combination is considered at a time until all combinations of components have been tested. However, this process may take a long time especially when there is a large number of components.

Hence, to determine the necessary components more efficiently, the experimental design method based on orthogonal arrays, can be used. This is a systematic and efficient approach to study the significance of each component of a system [5]. It studies the effect of each component simultaneously by using an orthogonal array requiring a minimum number of experiments. For example, a system with 3 components, a full factorial design requires 8 $\left(\text{i.e.: } 2^3\right)$ experiments. When the orthogonal design with the orthogonal array, $L_4(2)$ (shown in Table 1) is used, only four experiments are required in order to study the main effect of each component. Hence, four experiments $\left(\text{i.e.: } 8-4\right)$ or half the experimental time can be saved, compared with the full factorial design approach. The number of rows represents the experiments required to be performed. The number of columns represents the number of system components that need to be studied, where the experiments defined by the columns are mutually orthogonal.

In the orthogonal array, the '+' sign represents the corresponding component installed on the system, while the '-' sign represents the corresponding component that is not installed on the system. In the first row, there are three '+' signs. Hence, three components are installed on the system when conducting the experiment. In the second row, only the first component is installed on the system when conducting the experiment. In the third row, only the second component is installed on the system when conducting the experiment. Combinations in $L_4(2)$ have a pairwise balancing property, whereby every combination of components occurring in the experiments is the same. This minimizes the number of experiments required and enables a balanced study of the significance of each component.

A significant amount of experimental time can be saved when there is a large number of system components that need to be studied. . Table 2 shows an orthogonal array, $L_{14}(2)$ which it can be used for studying a system with fourteen components. When we use full factorial design, 16384 ($=2^{14}$) experiments need to be conducted. When the orthogonal array, $L_{14}(2)$, is used, only 20 experiments need to conducted in order to study the significance of each component. Hence, 16364 (=16384-20) experiments can be saved when we use $L_{14}(2)$ to conduct the experiments.

**Table 1** Orthogonal array ( $L_4(2)$ )

| Experiments | Component A | Component B | Component C |
|---|---|---|---|
| **1st** | + | + | + |
| **2nd** | + | - | - |
| **3rd** | - | + | - |
| **4th** | - | - | + |

## III. TRAFFIC FLOW PREDICTION USING ON-ROAD SENSORS

The on-road sensor configuration developed for a freeway is illustrated in Figure 1 where $n$ on-road sensors ($S_1$, $S_2$, …and $S_n$) are installed. Based on the traffic flow data captured by the on-road sensors, a traffic flow predictor can be used to predict the future traffic flow condition at location B, when drivers are in location A. It uses the traffic flow conditions collected by $S_i$, with $i$=1,2…,$n$ for performing traffic flow predictions, where $S_i$ captures the traffic flow condition, $y_i\left(t\right)$, in time $t$ with a sampling time of $T_s$ . Here the traffic flow condition is represented by the captured average speed of cars. If the speed approximates the freeway speed limit, the condition of the traffic flow on the freeway is smooth. If the average speed of the cars is far below the freeway speed limit, the traffic flow condition is not smooth and traffic congestion may occur. Therefore, when drivers are at location A and are managing to drive to location C as the destination, prediction of future traffic flow condition at B is useful. Drivers may directly go by the freeway, when the traffic flow condition at B is predicted to be smooth. Otherwise, they may use the small link to go to C and they can avoid the traffic congestion on the freeway, thereby saving on driving time.

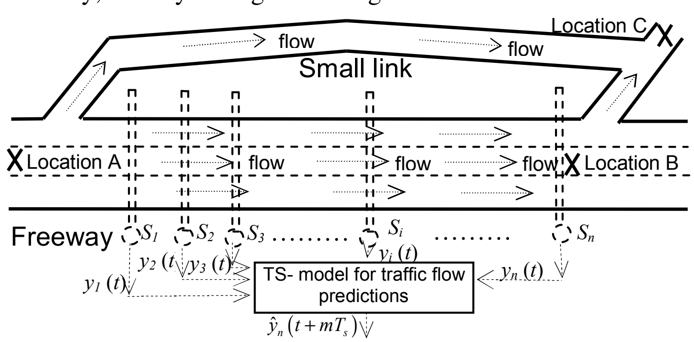


**Fig. 1** TS-model using on-road sensors on a freeway for traffic flow predictions

### A. *TS-model for traffic flow predictions*

In this research, the TS-model is used to predict the future traffic flow condition, $y_n\left(t+m\right)$, at location B with $m$ sample time ahead of the current time. It can perform the prediction by simply using all the current traffic flow conditions $y_1\left(t\right)$,

$y_2(t)$, …., and $y_n(t)$ captured by all $n$ sensors (i.e. $S_1$, $S_2$, …and $S_n$). However, not all the traffic flow data captured by the on-road sensors is significant for the TS-model to perform traffic flow prediction. We could imagine that the traffic flow data captured by $S_{n-1}$ is more significant than those captured by $S_1$, since $S_{n-1}$ is located much near to $S_n$ than $S_1$ does. Traffic flow conditions at $S_{n-1}$ are much more similar to those at $S_n$, while those at $S_1$ may not be similar to those at $S_n$, as they are separated by a larger distance. Therefore, using the traffic flow data captured at $S_1$ may not be helpful in predicting flow at $S_n$. We may need to select the appropriate on-road sensors which will give traffic flow prediction at $S_n$. However, in fact, it may not be always true that using the nearest on-road sensors is the best way. Determination of appropriate on-road sensor configuration is still necessary which will be illustrated on the case study in Section IV.

To develop the TS-model, it is essential to select the on-road sensors which are significant to traffic flow forecasting as the inputs of the TS-model for forecasting traffic flow at $S_n$. We assume that there are only $n_s$ on-road sensors that are significant to traffic flow predictions, and the $p(1)^{th}$, $p(2)^{th}$ ,..., and $p(n_s)^{th}$ on-road sensors are the significant ones. With the $n_s$ significant on-road sensor, the TS-model consists of $n_{rule}$ fuzzy rules, where the $g$-th fuzzy rule is given by:

$R_g$ : IF $y_{p(1)}(t)$ is $\mathrm{A}_{1,g}\left(y_{p(1)}(t)\right)$ AND $y_{p(2)}(t)$ is $\mathrm{A}_{2,g}\left(y_{p(2)}(t)\right)$

AND ..... AND $y_{p(n_s)}(t)$ is $\mathrm{A}_{n_s,g}\left(y_{p(n_s)}(t)\right)$

$$\text{THEN } z_g(t) = w_{0,g} + \sum_{i=1}^{n_s} y_{p(i)}(t)\cdot w_{i,g} \tag{1}$$

$g = 1,2,....,n_{rule}$ ; $y_{p(i)}(t)$, with $i = 1,2,...,n_s$, is the traffic flow condition captured by the $p(i)^{th}$ on-road sensor; as well as $p(i)\in[1,2,...,n]$ with all $p(i)\neq p(j)$ , $i,j = 1,2,...,n_s$ , but $n_s \le n$ .

For the $g$-th fuzzy rule in the TS-model, $w_{i,g}$ is the $i$-th polynomial coefficient, and $A_{i,g}\left(y_{p(i)}(t)\right)$, with $i = 1,2,...,n_s$, is the $i$-th membership function given as:

$$A_{i,g}\left(y_{p(i)}(t)\right) = e^{-\left(y_{p(i)}(t)-\bar{y}_{p(i),g}\right)^2 / 2\sigma^2_{p(i),g}} . \tag{2}$$

where $\bar{y}_{p(i),g}$ and $\sigma_{p(i),g}$ in equation (2) are the mean value and the standard deviation of the membership function respectively.

The membership grade for each rule is formulated as:

$$\mu_g(t) = A_{1,g}\left(y_{p(1)}(t)\right)\times A_{2,g}\left(y_{p(2)}(t)\right)\times ...\times A_{n_s,g}\left(y_{p(n_s)}(t)\right)$$

where $g = 1,2,....,n_{rule}$ . The predicted future traffic flow condition at $S_n$, $\hat{y}_n(t+T_s)$, is given by:

$$\hat{y}_n(t+m\cdot T_s) = \frac{\sum_{g=1}^{n_{rule}} \mu_g(t) z_g(t)}{\sum_{g=1}^{n_{rule}} \mu_g(t)}, \tag{3}$$

Based on equations (2) and (3), the functional relationship between $\hat{y}_n(t+m\cdot T_s)$ and all $y_{p(i)}(t)$ can be rewritten using equation (5), namely $f_{FNN}$ as:

$$\hat{y}_n(t+m\cdot T_s) = f_{FNN}\left(y_{p(1)}(t), y_{p(2)}(t),..., y_{p(n_s)}(t)\right) \tag{5}$$

Here, a widely-used approach with fast convergence, namely the ANFIS algorithm [3], is used to determine the parameters of the TS-models, $w_{i,g}$ , $\bar{y}_{p(i),g}$ , and $\sigma_{p(i),g}$ . It aims to optimize the following mean absolute relative error (namely, $e_{MARE}$ ), which is used to evaluate the generalization capability of the TS-model:

$$e_{MARE} = \frac{1}{N_{Data}}\sum_{k=1}^{N_{Data}} \frac{\left| y'_n\left(t(k)+m\cdot T_s\right) - \hat{y}'_n\left(t(k)+m\cdot T_s\right)\right|}{y'_n\left(t(k)+m\cdot T_s\right)} \times 100\% , \tag{6}$$

where $N_{Data}$ is the number of pieces of traffic flow data; and $\hat{y}'_n\left(t(k)+m\cdot T_s\right)$ is an estimate of the traffic flow condition with $m$ sampling time ahead, and $\hat{y}'_n\left(t(k)+m\cdot T_s\right)$ is given by:

$$\hat{y}'_n\left(t(k)+m\cdot T_s\right) = f_{FNN}\left(y'_{p(1)}\left(t(k)\right), y'_{p(2)}\left(t(k)\right),..., y'_{p(n_s)}\left(t(k)\right)\right).$$

The $k$-th piece of traffic flow data is given as:

$$\left[ y'_n\left(t(k)+m\cdot T_s\right), y'_{p(1)}\left(t(k)\right), y'_{p(2)}\left(t(k)\right),...,, y'_{p(n_s)}\left(t(k)\right)\right],$$

where $y'_{p(i)}\left(t(k)\right)$ is the traffic flow captured by the $p(i)^{\text{th}}$ on-road sensor at the time, $t(k)$, and $y'_n\left(t(k)+m\cdot T_s\right)$ is the average speed of cars collected from the $n^{th}$ on-road sensor at the time, $\left(t(k)+m\cdot T_s\right)$.

### *B. Design problem of TS-models*

The selection of on-road sensors affects the accuracy of the TS-model in predicting future traffic flow. The developed TS-model may be under-learnt when the traffic flow data of significant on-road sensors are not used on training. Hence, the resulting TS-model cannot address significant patterns of traffic flow. It cannot fully be trained with completed traffic flow patterns, and can only learn partial patterns for traffic flow forecasting. When too many patterns of insignificant on-road sensors are included for training, unnecessary effort is expended. Also, effective learning cannot be applied in the TS-model, since unnecessary patterns are likely to be fed into the TS-model. Hence, the learning of spurious patterns for traffic flow forecasting occurs in the TS-model.

To design an appropriate on-road sensor configuration, the trial and error method is generally used for selecting significant on-road sensors for traffic flow forecasting. We can obtain the global optimal configuration consisting of all significant on-road sensors by using full factorial design. However, this is impractical to test all on-road sensor configurations, as it may involve a large amount of evaluation time. For example, when there are only 10 sensors installed on the freeway, 1024 (=$2^{10}$-1) on-road sensor configurations need to be evaluated. Therefore, in the following section, we discuss a systematic and effective approach, based on orthogonal array, to determine the appropriate on-road sensor configuration.

## IV. ON-ROAD SENSOR CONFIGURATION DESIGN USING ORTHOGONAL ARRAYS

This section illustrates how the orthogonal arrays can be used to determine appropriate on-road sensor configuration for the TS-model. A case study is presented which involves a set of on-road sensors installed along the Mitchell Freeway, Western Australia.

### *A. On-road sensors installed on the freeway*

We studied the traffic flow conditions on a section of the Mitchell Freeway in Western Australia, which is the linkage between Reid Highway and Hutton Street. The on-road sensors (namely $S_1$ to $S_{14}$) shown in Figure 2 are used to captured traffic flow conditions, where the sampling time used for capturing the traffic flow conditions for these on-road sensors was 30 seconds. $S_1$, $S_2$ and $S_3$, were installed at the off-ramp, at the on-ramp, as well as between the off-ramp and on-ramp, for the Reid Highway respectively; $S_4$ and $S_5$, were installed at the off-ramp and near the on-ramp for Erindale Road respectively; $S_6$ to $S_{11}$, were installed at the off-ramp, near the on-ramp and between the off-ramp and on-ramp for Karrinyup Road, Cedric Street and Hutton Street respectively. The distance between the starting point (i.e. Reid Highway) and the ending point (i.e. Hutton Street) is 7 kilometers, and the freeway speed limit is 100 km/hr. Using the captured traffic flow conditions, the TS-model was developed to predict future traffic flow conditions with five sampling times ahead of the current time (or 2.5 minutes ahead).

In this case study, the traffic flow data used for developing the TS-model was collected in the 9th week of 2009. This data was collected during the morning peak traffic period (7.30-10.30 am) from Monday to Friday. This collected data was divided into two data sets, namely training set and test set. The training set was the data collected from the Monday to the Thursday. and was used to develop the TS-model. The test set was collected on the Friday. It was used to evaluate the generalization capability of the developed TS-model.

For the training set, the total time used for capturing traffic flow conditions from the Monday to the Thursday is 480 minutes (i.e. 4 days x 2 hours), as the sampling time used by the on-road sensors to capture traffic flow conditions was 30 seconds. Hence, the training set consists of 960 pieces of traffic flow data. For the test set, the total time used for capturing traffic flow conditions from the Friday is 120 minutes (i.e. 1 day x 2 hours). Hence, the test set consists of 240 pieces of traffic flow data.

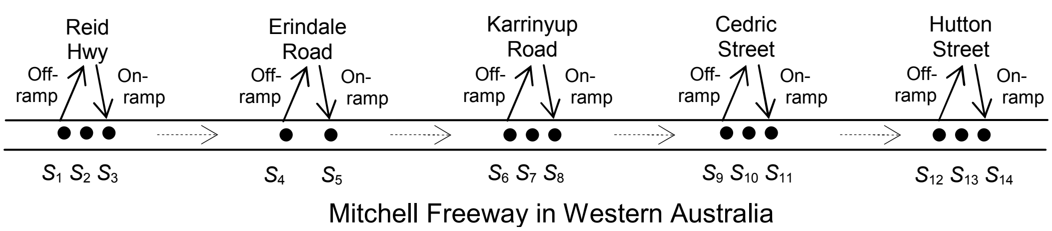


**Fig. 2** On-road sensor configuration on the Mitchell Freeway in Western Australia

### *B. Determination of orthogonal array*

This research aims to determine the appropriate on-road sensor configuration which can be used effectively on the TS-model for traffic flow forecasting. Hence, we need to determine which on-road sensors are needed to connect to the TS-model, and which on-road sensors are not needed. These connection or disconnection states of the on-road sensors can be designated as '+' or '-' conditions respectively. As fourteen on-road sensors were installed on the freeway, fourteen conditions with either '+' or '-' had to be considered.

In experimental design, these '+' or '-' conditions are the design parameters representing binary with either '+' or '-'. When the design parameter is '+', the corresponding on-road sensor is connected to the TS-model and the traffic flow conditions captured by this on-road senor are passed to the TS-model. When the design parameter is '-', the corresponding on-road sensor is disconnected with the TS-model and no traffic flow condition captured by this on-road sensor is passed.

An orthogonal array, $L_{20}(2^{14})$ given in Table 2, suits this design problem, since it involves 14 design parameters and 2 conditions (either '-' or '+'). With $L_{20}(2^{14})$, only 20 experiments need to be conducted to determine the appropriate on-road sensor configuration engaging 14 on-road sensors. As an example, the first experiment in $L_{20}(2^{14})$ is conducted by connecting all the on-road sensors with the TS-model. The second experiment is conducted by connecting the on-road sensors, $S_2$, $S_5$, $S_6$, $S_7$, $S_8$, $S_{10}$ and $S_{12}$ with the TS-model, while the other on-road sensors are all disconnected. Similarly, the rest of the experiments are conducted by connecting the on-road sensors when the entries are '+' and disconnecting those entries that are '-'

In this design problem, 16384 ( $= 2^{14}$ ) experiments need to be conducted to determine the appropriate on-road sensor configuration for the TS-model when full factorial design is used, as 14 design parameters with each design parameter having two states are studied. When the orthogonal array, $L_{20}\left(2^{14}\right)$, is used, only 20 experiments need to be conducted. Therefore, 16364 experiments ( = 16384 experiments - 20 experiments) can be saved by using $L_{20}\left(2^{14}\right)$.

If each experiment takes 40 seconds, the experiments using full factorial design will take a total of 654560 seconds (or 7.58 days) to complete. Using 7.58 days to develop a TS-model for traffic flow prediction is too expensive compared with using the orthogonal array which needs only 800 seconds for the completion of all the required experiments. Therefore, the orthogonal array approach requires much fewer experimental efforts than those required when using the full factorial design approach.

### C. *Experimental and analytical results*

The 20 experiments are conducted using 20 combinations of the orthogonal array, $L_{20}\left(2^{14}\right)$. Each combination represents an input configuration of the TS-model, while the states of the 14 on-road sensors need to be determined. These experiments aim to study the performance of the TS-models when different input configurations are used. With a particular input configuration, the TS-model can be developed by the training data. The generalization capability of the developed TS-model is evaluated by the test data using the mean absolute relative error, $e_{MARE}$, illustrated in equation (6), which represents the difference between forecasting of the traffic flow predictor and the actual traffic flow conditions. If $e_{MARE}$ is smaller, then the error between the actual traffic flow conditions and the forecasting is smaller. The results for all experiments are shown in Table 2, which illustrates the $e_{MARE}^{i}$ with $i = 1, 2, ..., 20$ obtained by the TS-model generated based on the $i$-th experiment.

| **Experiment** | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ | $S_8$ | $S_9$ | $S_{10}$ | $S_{11}$ | $S_{12}$ | $S_{13}$ | $S_{14}$ | **Number of on-road sensors installed** | $e_{MARE}^{i}$ (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1-st** | + | + | + | + | + | + | + | + | + | + | + | + | + | + | 14 | $e_{MARE}^{1} = 6.9223$ |
| **2-nd** | - | + | - | - | + | + | + | + | - | + | - | + | - | - | 7 | $e_{MARE}^{2} = 6.7981$ |
| **3-rd** | - | - | + | - | - | + | + | + | + | - | + | - | + | - | 7 | $e_{MARE}^{3} = 6.6742$ |
| **4-th** | + | - | - | + | - | - | + | + | + | + | - | + | - | + | 8 | $e_{MARE}^{4} = 6.8019$ |
| **5-th** | + | + | - | - | + | - | - | + | + | + | + | - | + | - | 8 | $e_{MARE}^{5} = 7.6281$ |
| **6-th** | - | + | + | - | - | + | - | - | + | + | + | + | - | + | 8 | $e_{MARE}^{6} = 7.9011$ |
| **7-th** | - | - | + | + | - | - | + | - | - | + | + | + | + | - | 7 | $e_{MARE}^{7} = 6.9194$ |
| **8-th** | - | - | - | + | + | - | - | + | - | - | + | + | + | + | 7 | $e_{MARE}^{8} = 6.9123$ |
| **9-th** | - | - | - | - | + | + | - | - | + | - | - | + | + | + | 6 | $e_{MARE}^{9} = 6.8804$ |
| **10-th** | + | - | - | - | - | + | + | - | - | + | - | - | + | + | 6 | $e_{MARE}^{10} = 7.8002$ |
| **11-th** | - | + | - | - | - | - | + | + | - | - | + | - | - | + | 5 | $e_{MARE}^{11} = 6.7681$ |
| **12-th** | + | - | + | - | - | - | - | + | + | - | - | + | - | - | 5 | $e_{MARE}^{12} = 7.3910$ |
| **13-th** | - | + | - | + | - | - | - | - | + | + | - | - | + | - | 5 | $e_{MARE}^{13} = 7.5855$ |
| **14-th** | + | - | + | - | + | - | - | - | - | + | + | - | - | + | 6 | $e_{MARE}^{14} = 7.1344$ |
| **15-th** | + | + | - | + | - | + | - | - | - | - | + | + | - | - | 6 | $e_{MARE}^{15} = 7.5739$ |
| **16-th** | + | + | + | - | + | - | + | - | - | - | - | + | + | - | 7 | $e_{MARE}^{16} = \underline{\mathbf{6.6774}}$ (smallest $e_{MARE}$) |
| **17-th** | + | + | + | + | - | + | - | + | - | - | - | - | + | + | 8 | $e_{MARE}^{17} = 7.6212$ |
| **18-th** | - | + | + | + | + | - | + | - | + | - | - | - | - | + | 7 | $e_{MARE}^{18} = \underline{\mathbf{8.1130}}$ (largest $e_{MARE}$) |
| **19-th** | - | - | + | + | + | + | - | + | - | + | - | - | - | - | 6 | $e_{MARE}^{19} = 6.8775$ |
| **20-th** | + | - | - | + | + | + | + | - | + | - | + | - | - | - | 7 | $e_{MARE}^{20} = 6.8634$ |

**Table 2** Orthogonal array, $L_{20}(2^{14})$, and experimental results

Table 2 also shows the number of on-road sensors connected with the TS-model. These results show that $e_{MARE}^{16}$ at the 16-th experiment is the smallest of all mean absolute relative errors, when the 16th experiment was involved with only seven on-road sensors. $e_{MARE}^{16}$ is smaller than $e_{MARE}^{1}$ obtained by the 1st experiment which involved all the fourteen on-road sensors. It indicates clearly that it is not appropriate to simply use all the on-road sensors to develop the TS-model for traffic flow forecasting. Using all sensor data might not achieve the best prediction result. Hence, it is essential to design an appropriate on-road sensor configuration for the TS-model in order to obtain accurate prediction for traffic flow conditions.

Since the combinations of the conditions of the on-road sensors are orthogonal, the main effects of each on-road sensor can be evaluated with respect to the two conditions, either '-' and '+' [5,8]. The main effects of each on-road sensor for each condition were calculated by adding all $e_{MARE}^{i}$ for the given condition. These calculations are shown in Table 3. As an example, the main effect of the on-road sensor $S_{10}$ at '+' condition is considered. It is connected with the TS-model on the 1st, 2nd, 4th, 5th, 6th, 7th, 10th, 13th, 14th and 19th experiments. The sum for all the '+' conditions is 72.3685, which is the main effect of $S_{10}$ at the '+' condition.

When all main effects of all on-road sensors are calculated, the significant of the on-road sensors can be computed by taking the difference between the largest and smallest main effects on a given on-road sensor. Table 3 also shows the significance of each on-road sensor. It indicates that the on-road sensor, $S_2$, has the highest significance. Hence, $S_2$ has the highest impact on the TS-model when it is connected with the TS-model. The on-road sensor, $S_6$, has the least significance to the TS-model. Hence, the impact on the TS-model is small whether this is connected with or disconnected from the TS-model. Also, Figure 3 shows graphically the main effects of each on-road sensor. It clearly shows the characteristics of the main effects and the significances of all on-road sensors. From the figure, we can observe that $S_4$ is more significant than all of the other on-road sensors, while the significance of $S_{13}$ is the smallest.

| | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ | $S_8$ | $S_9$ | $S_{10}$ | $S_{11}$ | $S_{12}$ | $S_{13}$ | $S_{14}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Condition '+' (connected)** | 72.4138 | 73.5887 | 72.2315 | 72.1904 | 70.8069 | 71.9123 | 70.3380 | 70.3947 | 72.7609 | 72.3685 | 71.2972 | 70.7778 | 71.6210 | 72.8549 |
| **Condition '-'** | 71.4296 | 70.2547 | 71.6119 | 71.6530 | 73.0365 | 71.9311 | 73.5054 | 73.4487 | 71.0825 | 71.4749 | 72.5462 | 73.0656 | 72.2224 | 70.9885 |
| **Significance** | 0.9842 | 3.3340 | 0.6196 | 0.5374 | 2.2296 | 0.0188 | 3.1674 | 3.0540 | 1.6784 | 0.8936 | 1.2490 | 2.2878 | 0.6014 | 1.8664 |

**Table 3** Main effects of each condition of each on-road sensor

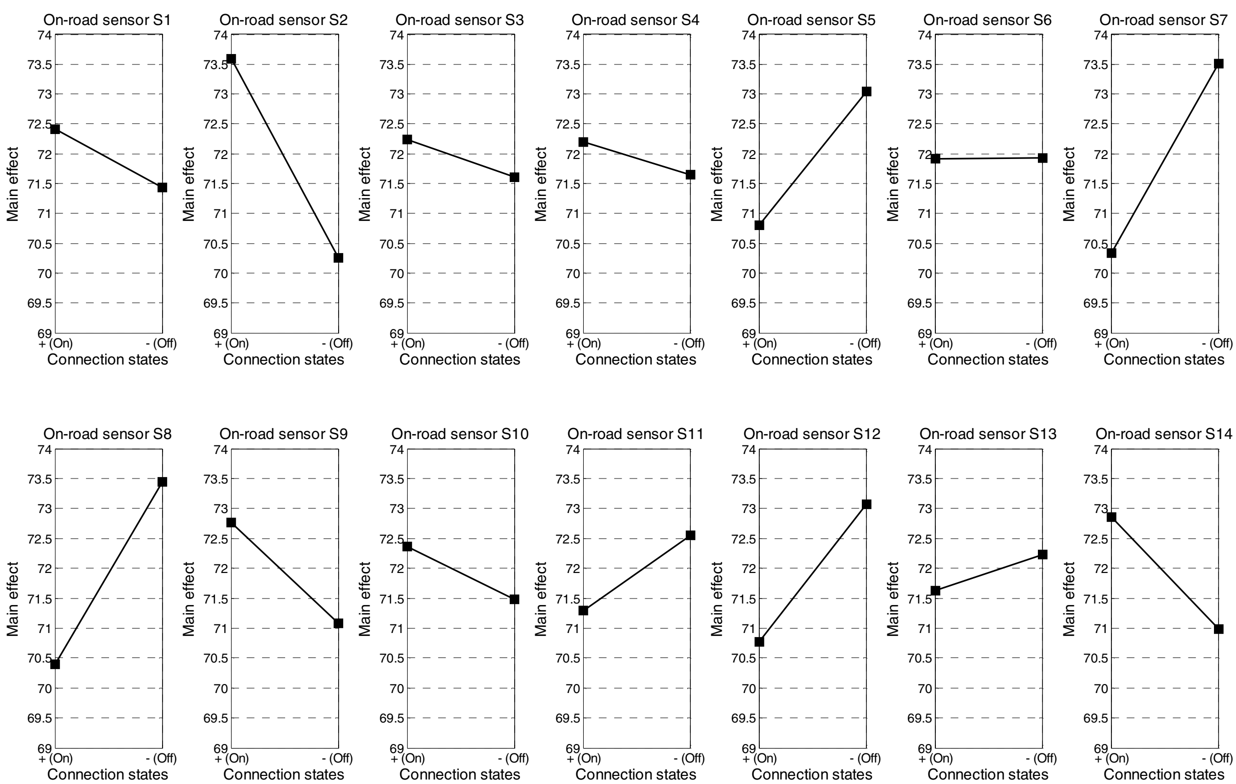


**Figure 3** Main effects of the on-road sensors

As the TS-model aims to provide an accurate forecasting of traffic flow, $e_{MARE}$ obtained by the TS-model is the smaller-the-better. Hence, we select the connection states of the on-road sensors with the smallest main effects. The underlined figures in Table 3 represent the small main effects of the on-road sensors. Therefore, seven on-road sensors are connected with the TS-model, i.e. $S_5$, $S_6$, $S_7$, $S_8$, $S_{11}$, $S_{12}$ and $S_{13}$ are connected. The rest of the on-road sensors are not connected wih the TS-model; hence, $S_1$, $S_2$, $S_3$, $S_4$, $S_9$, $S_{10}$ and $S_{14}$ are not connected. The simulation result obtained by the TS-model is shown in Figure 4. We can observe that the predicted traffic flow conditions are close to the real traffic flow conditions. The prediction error ($e_{MARE}$) is only 5.6419%, which is smaller than those obtained by the TS-models which were configured with the combinations of the orthogonal array, $L_{20}(2^{14})$.

Therefore, only seven on-road sensors need to be used by the TS-model for performing traffic flow forecasting. This is less than the total number of on-road sensors installed on the freeway and illustrates that it is not necessary to use all on-road sensors to develop the TS-model. In fact, it is more important to develop an appropriate on-road sensor configuration. With a simpler on-road sensor configuration, cost in terms of maintenance and effort can be reduced for the on-road sensor operation as, of the fourteen on-road sensors, only five need to be maintained. Also, the chance of generating faulty predictions can be reduced due to the wear or tolerance of the on-road sensors, as fewer on-road sensors are used in the TS-model.

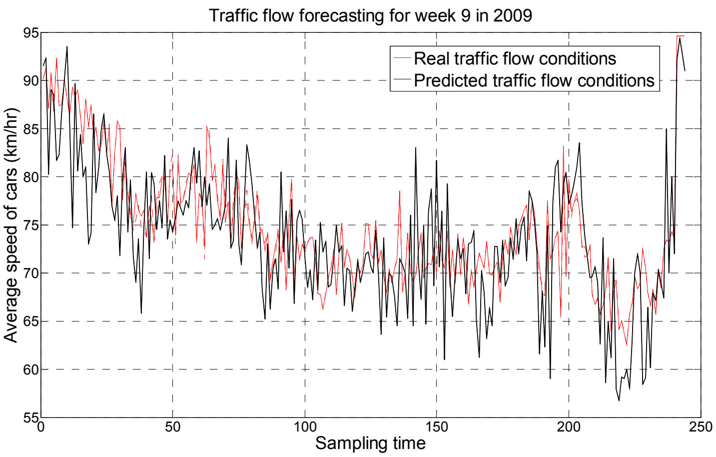


**Figure 4** Simulation results for the traffic flow forecasting

## V. Conclusion and Future Work

This paper presents an experimental design method, namely orthogonal array, to develop on-road sensor configuration for TS-models for traffic flow forecasting purposes. This design method is intended to select significant on-road sensors for TS-models, in order to forecast with more accuracy the traffic flow conditions. As the number of on-road sensors installed on the freeway is large, it is ineffective and impractical to test all individual configurations in order to determine the appropriate one. Hence, a systematic and effective experimental design methodology based on orthogonal arrays is proposed in order to determine appropriate on-road sensor configurations for TS-models. The effectiveness of using the orthogonal array was demonstrated by a case study on developing the TS-model for traffic flow forecasting, where the traffic flow data was captured by fourteen on-road sensors installed on Western Australia freeway. The case study illustrates that using the orthogonal array can provide a systematic and efficient methodology to determine the appropriate on-road sensor configurations. Also, far less development time is required than when using full factorial design. It also shows that a better TS-model with better traffic flow forecasting can be generated by analyzing the main effects of the on-road sensors. Apart from developing the TS-models, the methodology discussed in this paper can be applied to determine on-road sensor configurations for other intelligent forecasting systems such as neural network, fuzzy inference systems etc., since the forecasting performance of those intelligent systems can be poor when insignificant data is used for training.

In future, the two research directions will be focused. a) In this paper, the Taguchi method is only used for the design of TS-model. We will apply the Taguchi method to design the neural networks [17-19] which are effective for traffic flow forecasting. b) we will analyze the interaction effects between on-road sensors in developing the on-road sensor configuration. To do this analysis, an interaction effect plot [8] can be used by illustrating the main effects of the on-road sensors, and significant on-road sensors can be indicated. By doing this, better on-road sensor configurations are expected to be generated for the TS-models.

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