Introduction
Concrete is the most used construction material in the world and demand for concrete is ever increasing, regardless of geographical location. Fresh concrete is a perishable material and once the components of concrete are mixed, it must be dispatched as soon as possible. Due to space limitations at construction sites, as well as technical obligations, fresh concrete is frequently mixed at a Ready Mixed Concrete (RMC) depot and then hauled to construction sites via trucks. Therefore, to predict the duration of concrete pouring three kinds of parameters must be considered: (i) parameters that can reflect traffic patterns, (ii) parameters that can reflect supply situations, (iii) the parameters that represent the customer. This paper attempts to cover these three kinds of parameters in a cohesive dataset and then an advanced ensemble learning called Machine Learner Fusion-Regression (MLF-R) is hired to test the proposed method.

Contributions
- The two main contributions of this paper are: considering supply, traffic and customers representative parameters in predicting the duration of concrete pouring tasks; and implementing advanced ensemble learning. Beyond the construction sites there are important variables that have not been fully taken into account in predicting the productivity of concrete pouring. These variables will be integrated into the proposed model to predict the duration of concrete pouring more effectively. It is worth noting that the authors do not intend to estimate the size of the crew or machinery for concrete pouring, matters which have been discussed in literature extensively (46-54), but rather the focus is on predicting the duration of the process, which has not been sufficiently investigated to date.

Data Structure
This paper aims to consider both the execution and supply chain parameters related to concrete operations in the modelling process as well as some attributes that can represent traffic situations. Typically, fresh concrete is hauled by trucks from batch plants to construction sites and then placed in frames to construct concrete elements.

RESULTS
Due to the randomness issue, each method was run 10 times. The achieved results are summarized in Table 1. According to this table, MLF-R outperforms other methods in terms of RMSE. Although the means of the reported RMSE are almost the same, there is a significant difference (t-test) between the standard deviations of RMSEs of MLF-R and individual ANNs.

CONCLUSION
The results show that MLF-R obtained the least RMSE in comparison with other methods. Furthermore, MLF-R acquired the least standard deviation of RMSE and the correlation coefficient shows that this technique is less sensitive to the randomness issue and thus produces the least errors. This model can be used by both RMCs and clients for predicting the duration of concrete operations, thereby reducing idleness and the cost of equipment in construction sites.