

# **COST ESTIMATION OF HIGH PERFORMANCE CONCRETE (HPC) HIGH-RISE COMMERCIAL BUILDINGS BY NEURAL NETWORKS**

High-rise commercial buildings

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## **Abstract**

Neural network approach is applied to establish relationships between the quantities/cost of the concrete/formwork, which is required for the structural elements of tall buildings using high performance concrete (HPC), and the design variables. Hybrid and hierarchical strategies are proposed for the cost estimation, where the feed-forward networks are adopted. After training, the neural networks are utilized to predict automatically the quantities/cost of HPC wall-frame structures in tall commercial buildings. Verifications are conducted with respect to various sets of the design parameters and a comprehensive discussion is given.

Keywords: High performance concrete, cost estimation, high-rise buildings, neural networks

## **1 Introduction**

The costs of the high strength concrete (HSC) building structures are influenced by a number of factors, including the structure parameters (e.g., the grid size, the number of story and the grade of concrete), the building design specifications (e.g., the lateral drift of the building structure) and the design objectives (e.g., the minimization of total weights). Consequently, developing a model for cost estimation requires an intensive understanding of the relations between the above factors and the costs. Traditional approaches to cost estimation are mainly based on spreadsheets, database management systems (Bett, 1987), statistics (Wilson, 1982; Singh, 1994), linear regression (Koushoulas and Koehn, 1974; McCaffer, 1976; Bowen, 1985;



Singh, 1990). These methods are not appropriate for nonlinear multi-dimensional relationships involved in the cost analysis. Developing empirical or semi-empirical formulae through either simulated database (Singh, 1990, 1994) or the practical statistics (Karsheras, 1984) for the cost estimation of building structures is extremely difficult because of the highly coupled interaction among various factors.

Application of neural network approach to construction is a relatively new research area, including the modular construction decision making processes (Murtaza et al., 1994), construction cost estimation (Li, 1995a, 1995b), construction management (Chao and Skibniewski, 1994; Boussanaine, 1995; Li, Zeng and Guan, 1996), construction optimization (Flood and Kartam, 1994), construction bidding and forecasting (Gaarslev, 1991; McKim, 1993). In the development of neural cost models, Li (1995a, 1995b) explored the effect of network configuration on the accuracy of the models and discussed the difficulties in use of neural networks. The data for training the network was sampled from a bidding game. For predicting strength and workability properties of the fibre reinforced concrete (FRC) mixes, the feed-forward neural network has been employed (Rao, 1997), where the relations between the water-cement ratio, aggregate-cement ratio, aspect ratio and volume percentage of fibres, and the various strength parameters are learned. Hua (1996) applied neural network to forecast the demand for residential construction in Singapore, where a total of 12 economic indicators are identified as significantly related to demand for residential construction. It has been found that the neural network model can produce a better prediction than the conventional multiple regression.

In this paper artificial neural networks are applied to establish relationships between quantities/costs of the concrete/formwork for structural elements of tall buildings using high strength concrete and the design parameters. Two neural strategies of the cost estimation are proposed while the feed-forward neural networks are adopted. The trained networks are utilized to predict automatically the quantities/costs of high performance concrete (HPC) structures in tall buildings. Verifications are conducted and comparative analysis is given.

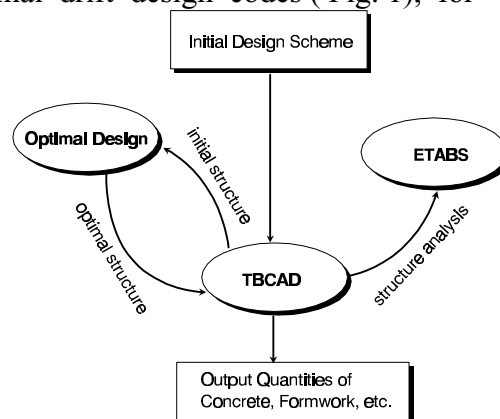
## **2 Neural cost estimation strategy**

### **2.1 Problem of the cost estimation**

The costs of concrete and formwork are directly proportional to their quantities required. The quantities are, however, affected by the structural design parameters such as grid sizes, grades of concrete, and numbers of stories. These costs and quantities can be found by using a structural design software package and computer calculation when the shape of the structure and its structural form are defined. In Hong Kong, the most common type of structural form for tall commercial buildings is the “Wall-Frame” structure which uses the shear wall construction to resist the lateral wind load and provides a centrally located service core to house utilities such as lifts, toilets and stairwells.

In this study, neural networks are anticipated to model the quantities/costs of

concrete and formwork required for the building structures, enabling designers to be aware of the design economy in adopting various design parameters such as concrete grades, grid sizes and numbers of stories. Direct collection of the cost data from practical statistics imposes some difficulties: expensive, time consuming and uncertain. The simulation approach is thus developed, by means of several software packages including TBCAD, ETABS, optimal drift design codes ( Fig. 1), for generating the database for cost estimation. The wall-frame structure, as shown in Fig. 2(a), is assumed for tall commercial buildings of 40 to 70 stories in this study, because it is the most common form of structure for tall buildings in Hong Kong. The fundamental structure members in the wall-frame structure systems involve solid slabs, beams, columns and shear walls. The simulation is based on the structural floor plan shown in Fig. 2(b). The whole structure is supposed to be constructed by HPC.



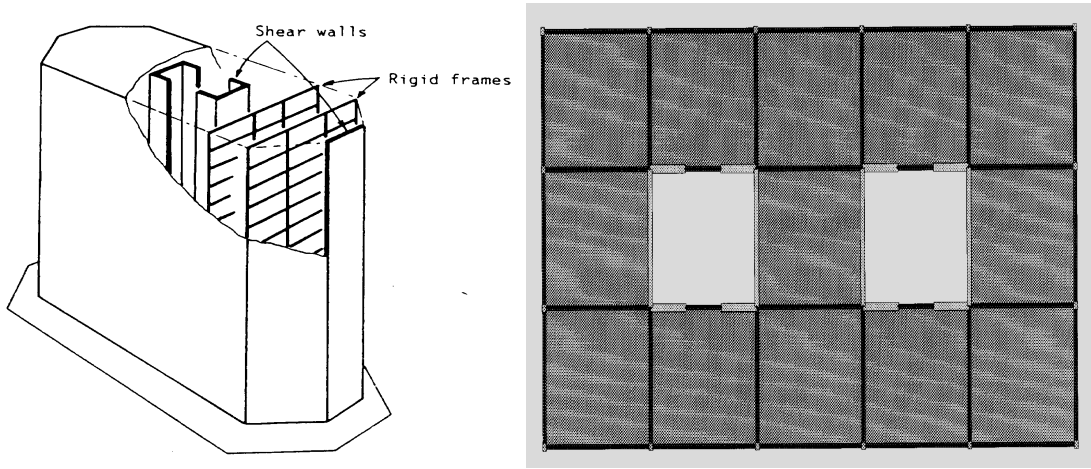
**Fig. 1: Sampling scheme of the database for cost estimation**

## 2.2 Hybrid cost estimation

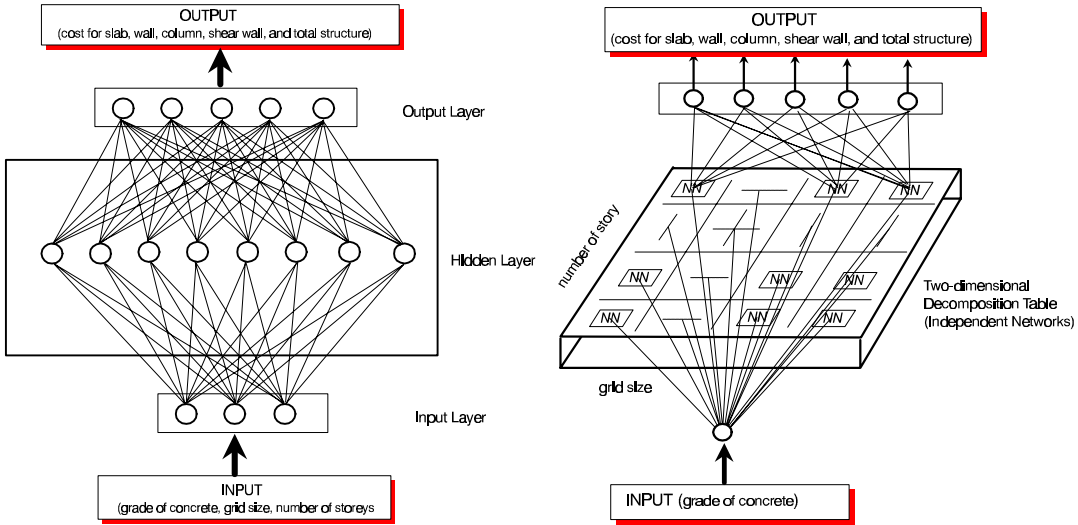
Given a set of input variables including the grid size, the number of story, the grade of concrete, one neural network can be used to estimate the costs for the concrete or formwork required for the structural elements (including the slabs, columns, beams and shear walls) and the whole structure. Fig. 3 presents this network-based hybrid model for cost estimation, where the network serves as a physical mapping between the input (independent) variables and the output (dependent) variables. However, the network may not be best suited to this multi-dimensional cost estimation problem, since the cost components to be estimated may have different sensitivities and variations with the input variables. Thus, the hybrid estimation model usually gives a compromised performance, although the training and implementation of the network require less computation.

## 2.3 Hierarchical cost estimation

The three inputs in the cost model above can also be decomposed by discretizing one or two independent variables into auxiliary variables. As such, the cost estimation can be carried out separately by a set of independent networks, leading to a hierarchical cost estimation scheme. Since networks are used to map relatively simpler input-output relationships, more suitable network configuration and learning parameters can be obtained and thus a better estimation performance can be attained.



**Fig. 2: Wall-frame structure and typical floor plan**



**Fig. 3: Hybrid neural cost estimation (Model I)      Fig. 4: Hierarchical neural cost estimation (Model II)**

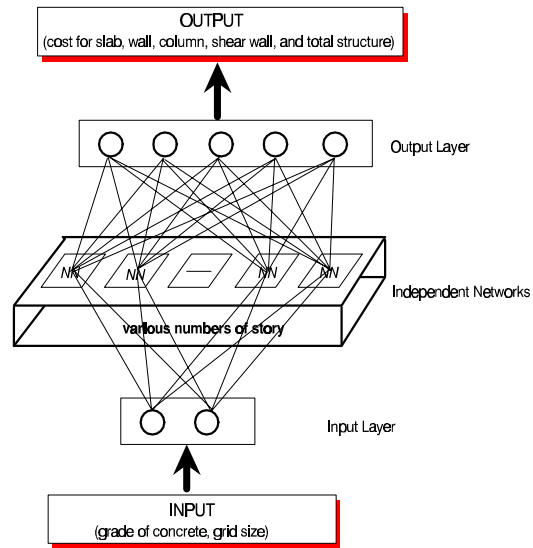
When two input variables are discretized into auxiliary variables, the cost model has only one independent variable. Given a pair of auxiliary variables, say the grid size and the number of story, a simple network with one input (the grade of concrete) can be employed to estimate the cost for the concrete and formwork, as shown in Fig. 4. Thus, a series of networks are required to cover entire ranges of the two auxiliary variables, with one network for each pair of the discretized variables. When another independent variable, say the grid size or the number of story, is selected, the network-based model similar to one shown in Fig. 4 can be applied.

When one independent variable is discretized into auxiliary variable, a network having two inputs can be used to estimate the cost for the concrete and formwork. With different variable as the auxiliary input, three hierarchical neural

models can be developed. Fig. 5 shows the hierarchical models for the costs with the number of story. In such models, a number of networks are needed to estimate the cost with respect to a particular discretized auxiliary variable. Each network has to be trained and applied independently.

### 3 Network construction and training

With respect to the hybrid model (Fig. 3), the input layer of the network has three neurons representing the grid size, the number of story and the grade of concrete, respectively, while the output layer has a total of five neurons representing the quantities of the concrete and the formwork for the slabs, columns, beams, shear walls and the whole structure. For the hierarchical models (Fig. 4 and 5), the inputs to the particular network depend upon the estimation scheme, while the outputs are the same as those for the hybrid model. There are one or two inputs when two or one input variables are discretized into auxiliary variables, respectively. As regards the number of hidden layers and neurons in each hidden layer, there is no general guideline for their selection. Associated with the hidden and output neurons are binary sigmoid transfer functions.



**Fig. 5: Hierarchical neural cost estimation (Model III) (with the number of story as the auxiliary)**

The feed-forward network is used to establish in an implicit manner the complex multi-dimensional mapping between the inputs and the outputs. Network training is to adjust the network weights to learn the training patterns, which is conducted by a commercial software NeuralWorks\* in this study. After training, the network can be instantly converted into a callable function for further implementation in the hybrid and hierarchical strategies.

\* The NeuralWorks is a product of NeuralWare, Inc., Pittsburg, PA 15276, USA.

## 4 Results and discussion

### 4.1 The training and testing patterns

The major objective of this investigation is to develop the neural network-based cost models, to realize the automatic cost estimation. To have such models, it is required to develop a comprehensive set of samples which cover ranges of independent variables influencing the cost of the HPC building structures. This is achieved in this study by conducting simulation experiments via the scheme shown in Fig. 1. The output obtained from the experimental simulations includes the quantities/costs for slabs, beams, columns, shear walls and the whole structure which are used as the desired target output for training the neural networks. The grade of concrete, the grid size, the number of story are chosen to be independent variables and sampled in ranges of (60-120MPa), (4-12m) and (30-70), respectively. Table 1 gives the quantities for the concrete of the structural elements, while the data for the formwork is omitted. There are a total of  $9 \times 5 \times 7 = 315$  training pairs.

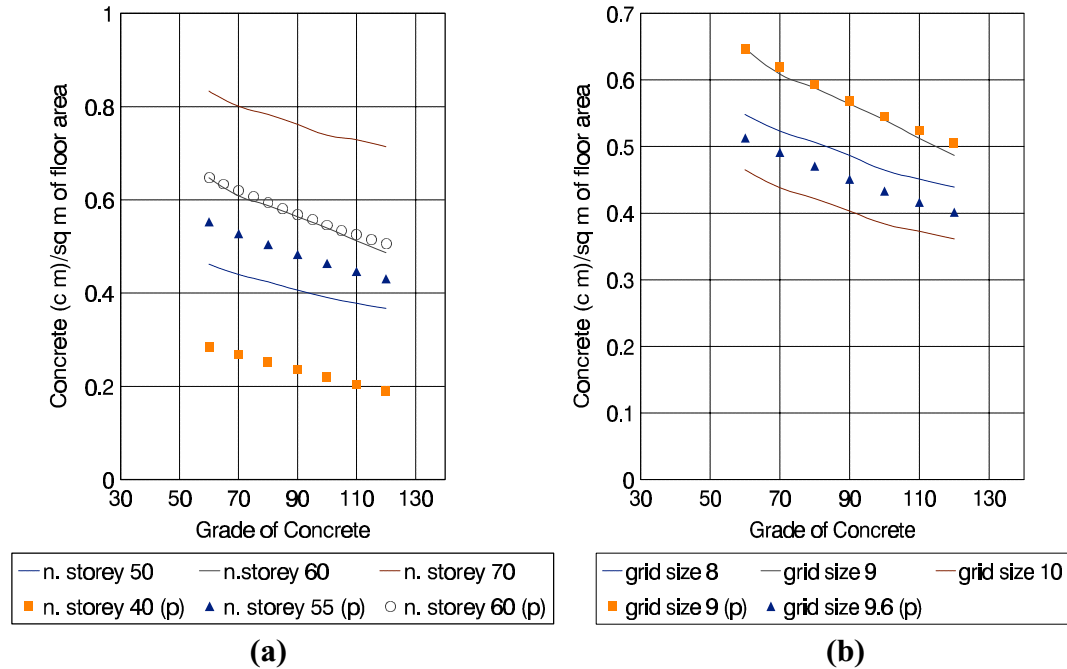
**Table 1 Training patterns for the networks for cost estimation of the concrete**

Input Patterns			Desired Output Patterns			
Grid Size (m)	Number of Story	Grade of Concrete (MPa)	Slab (cu m / sq m floor area)	Column (cu m / sq m floor area)	Beam (cu m / sq m floor area)	Wall (cu m / sq m floor area)
...	...	...	...	...	...	...
6	30	70	0.085896	0.030381	0.023374	0.060371
6	30	80	0.086041	0.023675	0.021465	0.054709
6	30	90	0.086260	0.019977	0.012665	0.050393
6	30	100	0.08649	0.017713	0.011579	0.043801
6	30	110	0.086569	0.009452	0.005277	0.038136
6	30	120	0.08662	0.006741	0.004915	0.034264
...	...	...	...	...	...	...
12	70	60	0.083870	0.128454	0.017954	0.151222
12	70	70	0.084042	0.108113	0.016845	0.143726
12	70	80	0.08416	0.098742	0.015910	0.138567
12	70	90	0.084322	0.094112	0.014956	0.132635
12	70	100	0.084417	0.086002	0.014082	0.124727
12	70	110	0.08463	0.082804	0.013213	0.119628
12	70	120	0.084789	0.078963	0.012369	0.116040

### 4.2 Results for hybrid cost estimation (Model I)

After a number of trial runs, it has been found that the network of two hidden layers, having 10 neurons each, can achieve a better training performance of the converging error of 0.08. Hence, such a network is finalized for the hybrid cost model. The validation and testing results are plotted in Fig. 6, with respect to various combinations of the grid size, the number of story and the grade of concrete. Fig. 6(a) shows the estimated cost of the whole concrete, for the numbers of story of 40, 55 and 60, varying with the grade of concrete, given a fixed grid size of 9m. The estimated

costs for the number of story of 60 is found to agree uniformly with the desired ones. The estimated costs for the number of story of 55 have clear reasonable trends of variations and are well interpolated. Fig. 6(b) presents the validation results for the grid sizes of 9m and 9.6m with respect to different grades of concrete, given the number of story of 60. Satisfactory agreement of the estimated costs with the desired ones and excellent interpolation of the neural estimation have been confirmed.



**Fig. 6: Validation results for hybrid cost estimation (Model I) for the concrete**

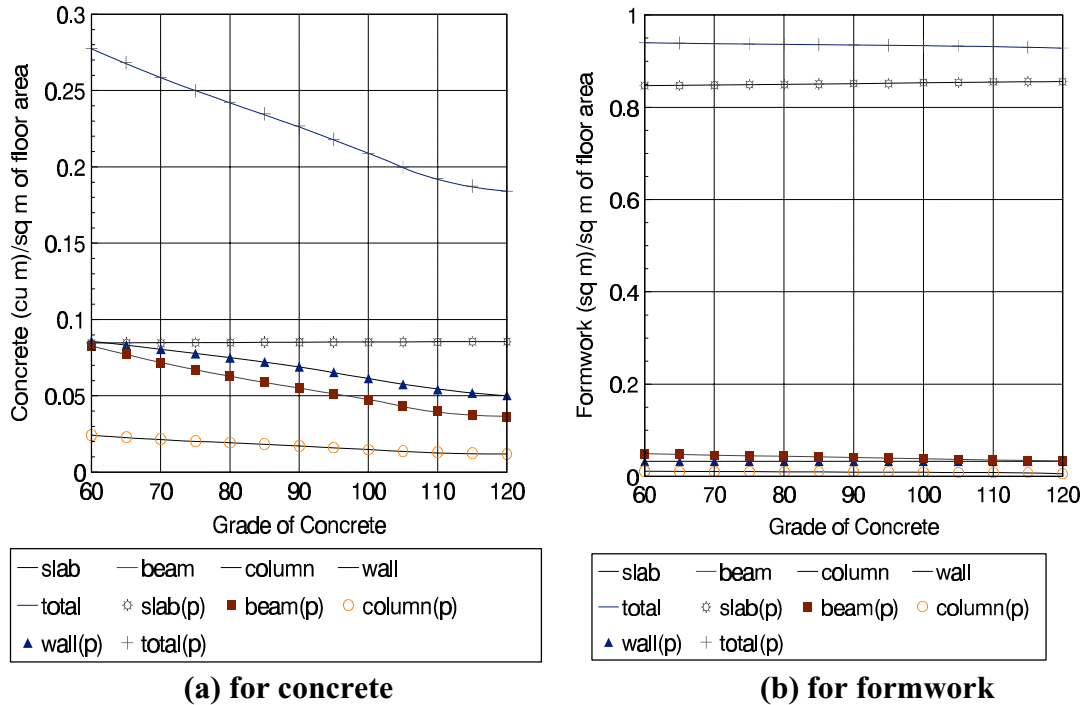
#### 4.3 Results for hierarchical cost estimation (Model II)

With respect to the estimation model (Fig. 4), a number of networks are required for different pairs of auxiliary variables. In this work only one network for the particular grid size of 9m and number of story of 40 is given as an example. For this model there are one input and five outputs. After numerous trial runs, the network configuration of one hidden layer with five neurons has been adopted, with the converging error of 0.02. The validation results for the costs of the concrete and the formwork are presented in Fig. 7. The promising estimations have been found.

#### 4.4 Results for hierarchical cost estimation (Model III)

When the number of story is taken as auxiliary variable, the hierarchical strategy can be realized using the Model III (Fig. 5). A number of networks with two inputs and five outputs are required to estimate the costs for concrete and formwork, with one network for each fixed number of story. In this case, there are a total of  $9 \times 7 = 63$  training patters, with respect to the grid sizes of 4, 5, ... and 12, and the grades of concrete of 60, 70, ..., 110 and 120. The network configuration of two hidden layers with 10 neurons each has been adopted after a few of trial runs. The converging errors are about 0.01 and 0.02 for the networks for the concrete and

formwork, respectively. Fig. 8 shows the validation results for the cost of the total concrete and formwork, for the discretized number of story of 60, with respect to various grades of concrete. The estimation has been found excellent for the costs of the whole structure concrete. The estimated costs for the grid size of 9m fall uniformly on the curve for the desired costs. The estimated costs for 9.6m look well interpolated between the curves for both grid sizes of 9m and 10m. However, the errors associated with the estimated costs for the total formwork look quite larger. The desired variation of the cost in the range of the grades of the concrete of 60MPa and 80MPa has been smoothed off in the neural model.



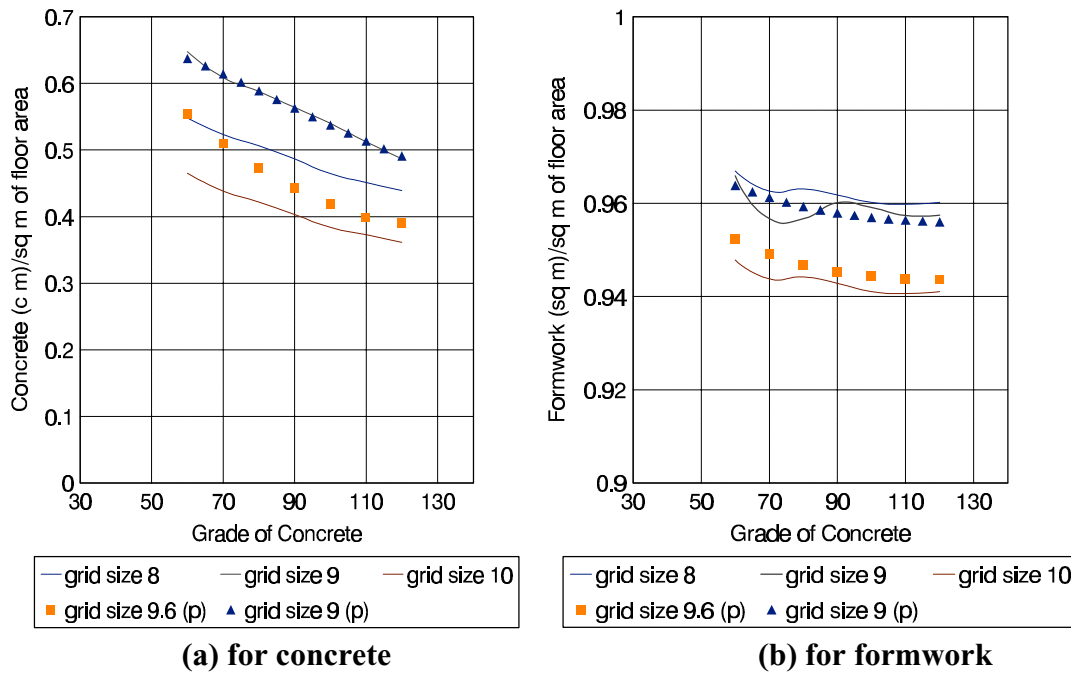
**Fig. 7: Validation results for the cost estimation (Model II)**

#### 4.5 Comparative analysis

Adopting the hybrid estimation strategy, only one neural network is required and trained. It has been confirmed from the training results that the network (for both concrete and formwork) has the best converging accuracy of 92%, which is smaller than the training results of the hierarchical strategy. The major advantage of the hybrid strategy for the cost estimation is easy to implement. Thus, if the average estimation error of 0.08 is acceptable, the estimation strategy is suggested.

For achieving a better estimation accuracy, the hierarchical strategy is suggested. The training as well as estimation performance of the hierarchical strategy varies from one model to another. It is found that the model II and model III give better estimation performance with accuracy of 0.01 and 0.02. However, as the hierarchical estimation strategy requires more than one network, more training and implementation work is necessary.





**Fig. 8: Validation results for the cost estimation Model III  
(with the number of story being auxiliary variable at 60)**

## 5 Conclusion

Using the quantities/cost data for the structure elements generated from the structure analysis, neural networks can be employed to predict automatically the costs of concrete and formwork required for a wall-frame structure system of tall commercial buildings using high strength concrete. The structural elements involve solid slabs, beams, columns and shear walls. Design parameters such as grid sizes, numbers of story and grades of concrete have been considered in the models to assess their effect on quantities/costs of the HPC structures. Two strategies of cost estimation based on neural networks have been proposed. From the training and validation results, it can be concluded that all the neural models, no matter of the hybrid or hierarchical strategies, can provide a promising cost estimation. The two strategies are compared and it is confirmed that the hybrid model is less accurate but easy to be trained, while the hierarchical models are more accurate but more complicated in implementation.

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