UTILIZATION OF NEURAL NETWORKS FOR SIMULATION OF VEHICLE INDUCED FLOW IN TUNNEL SYSTEMS

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ABSTRACT

UTILIZATION OF NEURAL NETWORKS FOR SIMULATION OF VEHICLE INDUCED FLOW IN TUNNEL SYSTEMS

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Air velocities induced by underground vehicles in complex metro systems are obtained using artificial neural networks. Complex tunnel shaft-systems with any number of tunnels and shafts and with most of the practically possible geometries encountered in underground structures can be simulated with the proposed method. A single neural network, of type feed-forward back propagation, with a single hidden layer is trained for modelling a single tunnel segment. Train and tunnel parameters that have influence on the vehicle induced flow characteristics are used together to obtain non-dimensional input and target parameters. First input parameter is the major head loss coefficient of tunnel, $(L/D)_{Tunnel}$. Blockage ratio A_{Train}/A_{Tunnel} and train aspect ratio $(L/D)_{Train}$ are selected to be non-dimensional input parameters to represent the system geometry. As the final input parameter, skin friction coefficient of the train, f_{Train} drag coefficient of the train, C_D; frontal area of the train, A_{Train} and lateral area of the train, $A_{Lateral}$ are combined into a single overall drag coefficient based on the train frontal area. Non-dimensional V_{Air} / V_{Train} speed ratio is selected to be the target parameter. Using maximum air velocity predicted by the trained neural network together with non dimensional system parameters and time, an additional neural network is trained for predicting the deceleration of air in case of train stoppage within the tunnel system and departure of the train from the system. A simulation tool for predicting time dependent velocity profile of air in metro systems is developed with the trained neural networks.

Keywords: piston effect, incompressible flow, vehicle induced flow, neural networks, transient air velocity

ÖZ

TÜNEL SİSTEMLERİNDE ARAÇ KAYNAKLI HAVAHIZLARININ YAPAY SİNİR AĞLARI KULLANILARAK MODELLENMESİ

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Karmaşık metro sistemlerinde araç kaynaklı hava hızları yapay sinir ağları kullanılarak elde edilmiştir. Önerilen yöntemle, yer altı ulaşım yapılarında karşılaşılabilecek geometrik düzenlemelerin birçoğunun bulunduğu karmaşık sistemlerin modellemesi yapılabilmektedir. Tek bir tünel içerisinde hareket eden bir trenin modellenmesi için, bir gizli katmanı olan, ileri beslemeli, geriye yayılımlı bir yapay sinir ağı eğitilmiştir. Araç kaynaklı hava akışında etkisi olduğu bilinen parametreler, boyutsuz değişkenler elde etmek amacıyla farklı gruplar halinde bir araya getirilmişlerdir. Bu sayede yapay sinir ağı için boyutsuz girdi ve hedef parametreleri elde edilmiştir. İlk boyutsuz girdi parametresi, tünelin majör kayıp katsayısı olan $(L/D)_{Tunnel}$ terimidir. Tren blokaj oranı A_{Train}/A_{Tunnel} ve tren uzunluğunun hidrolik çapına oranı $(L/D)_{Train}$ sistem geometrisini tanımlamak için kullanılan diğer iki boyutsuz parametredir. Son boyutsuz girdi parametresi olarak, tren yüzey sürtünme katsayısı, sürükleme katsayısı, yanal alanı ve ön kesit alanı bir araya getirilerek elde edilen tren sürtünme katsayısı kullanılmıştır. Boyutsuz hız

oranı, V_{Air}/V_{Train}, yapay sinir ağları için kullanılan hedef parametresi olarak kullanılmıştır. Yapay sinir ağı ile elde edilen en yüksek hava hızları, boyutsuz sistem parametreleri ve zaman değişkeni ile birlikte kullanılarak, trenin sistem içerisinde durması ya da sistemi terk etmesi durumunda hava hızının sönümlenmesini modelleyen ek bir sinir ağının eğitilmesinde kullanılmıştır. Eğitilen yapay sinir ağları ile, metro sistemlerinde zamana bağlı hava hızlarının elde edilmesini sağlayan bir simülasyon aracı geliştirilmiştir.

Anahtar Kelimeler: Piston etkisi, sıkıştırılamaz akış, araç kaynaklı akış, yapay sinir ağları, zamana bağlı hava hızı

To My Naive Family

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A	: Cross Sectional Area	[m^2]
$A_{lateral}$	: Train Lateral Area	[m^2]
A_{tunnel}	: Tunnel Cross Sectional Area	[m^2]
A_{train}	: Train Frontal Area	[m^2]
A_{An}	: Area of the Annulus between Train and Tunnel Walls	[m^2]
C_D	: Train Drag Coefficient Based on Frontal Area	
$C_D\_overall$	: Overall Train Drag Coefficient	
D_h	: Hydraulic Diameter	[m]
f_{train}	: Train Skin Friction Coefficient	
f_{tunnel}	: Tunnel Wall Friction Factor	
P	: Pressure	[Pa]
K_{eq}	: Equivalent Head Loss Coefficient for Tunnel-Shaft System	
K_t	: Total Head Loss Coefficient for Tunnels	
K_s	: Total Head Loss Coefficient for Shafts	
K_{sm}	: Minor Head Loss Coefficient for Shafts	
k_{tunnel}	: Minor Head Loss Coefficient for Tunnels	
k_{shaft}	: Minor Head Loss Coefficient for Shafts	
L_{train}	: Train Length	[m]
L_{tunnel}	: Tunnel Length	
S_{tr}	: Train Perimeter	[m]
S_{Tun}	: Perimeter of the Tunnel Cross Section	[m]
R^2	: Coefficient of Determination	
t_{flat}	: Time for Steady State Air Velocity	[s]
$t_{\max}$	: Time of Maximum Air Velocity	[s]
V_{air}	: Time Dependent Velocity Profile	[m/s]
V_{tr}	: Time Dependent Train velocity	[m/s]
v_{aver}	: Average Air Velocity	[m/s]
$v_{\max}$	: Maximum Induced Air Velocity	[m/s]
Q_T	: Total Flow Rate Occurring in a Tunnel	[m^3/s]
Q_t	: Flow in a Tunnel	[m^3/s]
Q_s	: Flow in a Ventilation Shaft	[m^3/s]

Greek Letters

β	: Non-dimensional velocity	
ρ	: Density of Air	[kg/m^3]
σ	: Blockage Ratio	
Γ	: External Friction Forces acting on Air	[m/s^2]

Abbreviations

CFD : Computational Fluid Dynamics
ANN : Artificial Neural Networks
SES : Subway Environmental Simulation Software
NFPA : National Fire Protection Association
PIARC: World Road Association
NDF : Non-dimensional Friction
NDT : Non-dimensional Time
NH : Number of Neurons in Hidden Layer
NI : Number of Neurons in Input Layer
NP : Sample Size
Re : Reynolds number

CHAPTER 1

INTRODUCTION

1.1 Background

Mass transport is one of the most attractive means when energy saving crave of the world is considered. Many cities are on their way to switch to underground transportation in order to be able to relieve the congestion due to ground vehicles and reduce the amount of exhaust emissions. For this purpose, huge amount of design and construction of metro lines are still in progress. Two important concerns about a metro system design are safety and the comfort level sustained during train operations since there are comfort limits for air velocities and pressures in closed occupied areas [1]. Major means that has effect on comfort level in metro systems is the vehicle induced air velocity and pressure.

Vehicles travelling inside tunnels induce air flow, which is basically driven by the moving boundaries of the vehicle. This phenomenon is known as “piston effect”. What actually piston effect is the flow of air being pushed by the frontal and lateral area of the train in the direction of motion. For a stationary observer located on the platform of a station, piston effect can be observed as follows.

- A little amount of air velocity is felt just before the train enters the station.
- Air velocity increases to its maximum value during the deceleration of the train just before complete stop.

- Air velocity starts to decrease while the vehicle is on a halt and dwelling for the passengers entraining and detraining.
- Following the acceleration for the train after its dwell, air velocity starts to build up again. This time the observer may expect a fresher air than before since the second velocity build up is majorly due to the air being sucked from ventilation structures and staircases.
- As soon as the vehicle leaves the station, air velocity starts to decrease again until the next train induces the same sequence of events.

Taking piston effect and thus abovementioned sequence of events into account at design stage of metro systems is mainly considered as an optimization problem in searching the minimum construction cost together with the operation cost. Air flow induced and brought to the stations by the moving trains contributes to the air exchange of the stations which is a desired effect. More natural ventilation means fewer requirements for additional ventilation and air handling equipments like air conditioners, fans and air handling units.

On the other hand, while maximizing the amount of air flow that contributes to the air exchange, designers should also keep the maximum air velocity on the platform level under a certain value. Limit values of air velocity in occupied regions in metro systems are defined either by international codes and standards or local regulations.

For optimizing design, proposed solution by the metro system designers is placing ventilation shafts at the entrance and exits of the stations. These shafts, in addition to their duty for emergency ventilation, serve as air flow shortcuts connecting the station structure to the ground level. This way, excess amount of air can be got rid of through these openings and air velocities on platform level can be controlled. Jia et al. [2] showed in their numerical simulations of flow characteristics in subway stations that, ventilation shafts placed before and after the station has great effect on augmenting the ventilation characteristics of the station while reducing the air velocities encountered in the station. Ventilation shaft at the entrance of the station is termed as a "blast shaft" since it basically dampens the effect of positive pressure that builds up in train front. At the exit of the station, there installed "relief shafts" which are responsible for relieving the negative pressure at the train rear while train leaves the station. These shafts serve in a reverse manner when a train approaches from the opposite direction to the station. Ventilation shafts can be considered as similar to open surge protection structures in liquid pipelines.

Although ventilation structures, at a first glance, seem to be the solution of the optimization problem in metro system design, it is not a straight forward procedure to design and implement the correct ventilation shaft structure. First of all, introduction of a ventilation shaft to a station may lead one of the following two effects;

- Ventilation shaft may serve as intended and may let the required amount of air through. This way, maximum air velocity on the platform level induced by the trains can be controlled.
- If not designed properly, ventilation shaft may decrease the system resistance to air flow to very low values which results in more amount of train induced air flow. This would result in even higher air velocities than a case without a ventilation shaft.

So, a ventilation shaft cannot be considered as just a simple opening to atmosphere but requires a systematic engineering approach for being properly designed.

Engineers can make necessary calculations and modifications on system design with some analytical means but, since metro systems are complex flow networks, it is almost impossible to predict the net effect of a modification on the overall system performance as long as the full system is not considered at a time. This optimization effort makes piston effect simulations crucial.

For the purpose of a proper system design and for sake of energy efficiency and optimization, during design stage of a metro system, numerous computer simulations for piston effect are run. Each simulation with the current state of the design provides possible improvement opportunities and designer can modify or change the design being done.

Computer simulations for piston effect are done in 1D because the sizes of the flow domain in complex metro systems are impractically large to be modelled and solved in 3D CFD software. High length to hydraulic diameter ratio encountered in metro structures also allows one dimensional approach.

Modelling in 1D requires a careful investigation of the structures in the metro system. Since it is impossible to incorporate all details of structures in the system to one dimensional model, these details should be introduced to the model through use of minor head loss coefficients for different flow structures. Minor head loss coefficients are obtained from empirical relations and tabulated data present in the literature.

One dimensional modelling and simulations can be done using software packages that have the moving boundary feature. Subway Environmental Simulation (SES) Software is one of these software and is one of the most commonly used all around the world. One can use SES for both piston effect and emergency ventilation simulations. In most of the metro system design work around the world and in each and every metro project in Turkey, SES Software is the only tool that is accepted by the authorities. Although a few design groups have this software, it is not commercially available at the moment and there is not any alternative software that can be considered as a substitute. In this study, a tool that can be used as a replacement to SES is developed using artificial neural networks.

Artificial Neural Networks (ANN) are data driven methods which originated from the basics of the neurobiological systems. Early attempts on neural networks are from 1940's. Although neural network approach was getting popular, revealing of deficiencies in neural network approach in 1969 had a negative effect on the interest given to this area. By the emerging of back propagation algorithm for neural network training and solution of some drawbacks, neural networks regained more attraction again [3].

Haykin [4] gives a formal definition of neural network as "a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented by using electronic components or simulated in software on a digital computer". Neural networks are supposed to acquire information from their environment and store them by use of weights. Major advantages of neural networks are their ability to "learn" and computational efficiency arising from their parallel nature. They are used for function approximation, data processing, clustering, time series prediction and regression in the fields of fluid mechanics, heat transfer, information technologies, control, computer science, economics, natural sciences and many other. Neural networks can be used for approximating physical phenomena by the use of field data. Laboratory or field measurements can be used for neural network training and effect of varying parameters can be approximated with neural networks. Training a neural network with field data is not the only way of using a neural network. Simulation data, most of the time produced by computer software, can also be used for neural network training which can be eventually considered as Meta modelling. In this thesis, neural networks are trained with the data produced by SES computer software.

There are three fundamental types of neural networks namely, single layer feed forward, multilayer feed forward and recurrent. Different applications demand different types of neural networks in representing the actual physical phenomena. In this thesis, through a systematic assessment and referencing to literature, single and multi layer feed forward neural networks are utilized based upon their ability to approximate continuous functions.

Basic processing unit of a neural network operating on the input data is known as a neuron, structure of which is presented in Figure 1-7. The neuron receives N number of inputs. In a single neuron, a transfer function is applied on the weighted sum of these inputs to generate an output, which is expected to approximate the desired target. Many neurons can be connected in parallel to form a layer and many layers can be used in series to form a multilayer network. Transfer functions can be of linear, threshold or sigmoid types. For mapping a continuous function between the inputs and outputs, sigmoid type transfer functions are used, as done in this study.

Learning of a neural network can be supervised or unsupervised. In this study, supervised learning, which implies presence of a teacher, is adopted. In supervised learning an output set is available and neural network maps a function between the input and output data by iteratively adjusting weights of each individual input until a desired accuracy of neural network generated outputs evaluated against actual outputs is obtained.

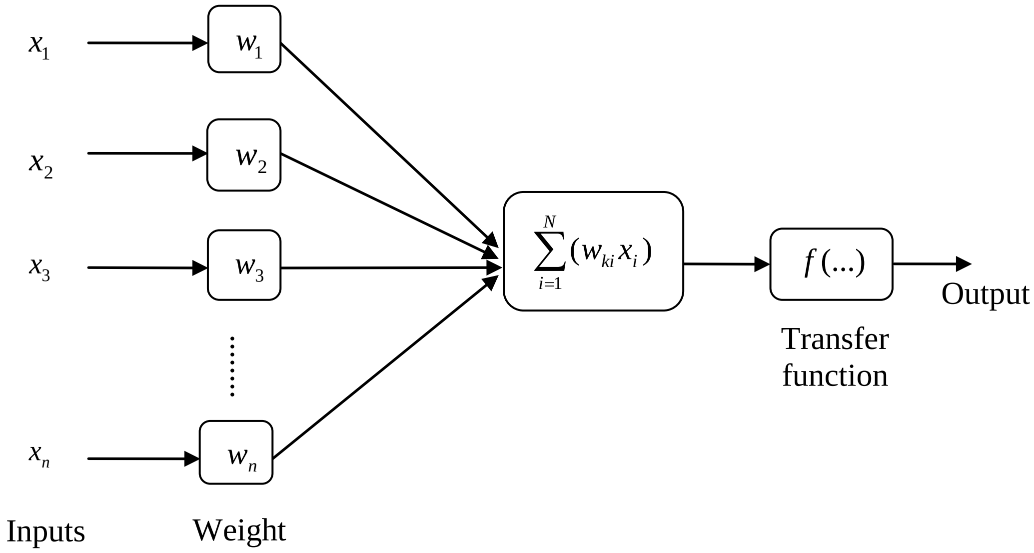


Figure 1-1 Structure of a neuron

A neuron, presented in Figure 1-1 can be described as follows;

- Input signal x_i is connected to the neuron k is first multiplied by the weight w_{ki}. One should note that the subscript i refers to the weight of the input signal and the subscript k refers to the neuron in question.
- A summation function is applied to all input signals which are already multiplied with their corresponding weights.
- Activation function f, which is also referred to as squashing function, is applied over the weighted input signal and limits the amplitude of the output to finite values.
- Activation function generates the results of the neuron which will be compared with the target data during training.

Note that, a feedback route between the outputs generated by the activation function and any layer of the neural network can be present in case it is known that the output has effect on itself or in other words the system is dynamic. For such cases, neural network structures with memory or feedback are used and are referred to as recurrent neural networks. In this thesis, feed-forward neural networks are used after an assessment of the nature of the physical phenomena involved. Details of the neural network selection are presented in Chapter 2 of the thesis.

In addition to structure of the neural network and its activation functions, learning algorithms used in training has also great influence on neural network performance. Learning of a neural network can be classified with two major types; supervised and unsupervised learning.

In supervised learning, there exists a target data in comparison with which the error of the neural network generated results is calculated. With the calculated error, weights of the neurons are modified until the desired output can be obtained by the neural network. In unsupervised learning, also referred to as *learning without teacher,* there is not any output data with which the results of the neural network is compared during training for error calculation. In this type of learning, neural network basically tries to find a hidden structure within the input data. Self Organizing Maps (SOM) is one of the commonly used unsupervised learning algorithms.

In the content of this thesis, supervised learning is applied in presence of input and target data together. Vehicle induced air velocity results from SES Software are used as the target data and supervised learning of the trained neural networks is managed.

1.2 Literature Survey

1.2.1 Piston Effect and One Dimensional Flow

There is a huge amount of effort on understanding and application of one dimensional flow both in compressible and incompressible flow regimes. To be able to design and operate underground transportation systems including moderate speed trains, high speed trains and even passenger cars and load trucks, valuable theoretical and experimental studies are stated in literature. One can see that, most of the studies cover the basics and aims solving some practical problems commonly encountered during operation or design of underground structures.

Finding the ways of increased transportation efficiency is one of the most significant efforts in this field. To increase the transportation efficiency, there are great effort in fields of aerodynamics of vehicles and structures, while most of the train manufacturers still search for faster and lighter trains. Raghunathan et al. [5] states in their study that, current effort on speeding the high speed railway trains up ignores the essence of the aerodynamics which should be considered prior to developments of better electric motors that drive these trains. They presented the state of the art aerodynamics of tunnels and trains and they presented valuable indexes that correlate vehicle characteristics to aerodynamic forces on the vehicles. One of the parameters that affect the aerodynamics of tunnels is the blockage ratio of the train. Patil et al. [6] considered the effect of blockage ration on wake transition in case of flow past a cylinder. They studied the effect of wall confinement on wake characteristics like shear layer behaviour. With their two dimensional simulations they concluded the effect of blockage ration on critical Reynolds Number and Strouhal Numbers.

There are numerical and approximate analytical methods that can be used to predict air velocities induced by a metro vehicle with the given geometric and dynamic characteristics like frontal cross sectional area, speed of the train drag coefficient, etc. Jang et al. [7] conducted experimental studies on Fu-De Tunnel in Taipei City for determination of aerodynamic coefficients of the tunnel. They took measurements of air velocity inside the tunnel in various traffic conditions and obtained values for tunnel friction factor and drag coefficient of small and medium sized vehicles. They concluded that, obtained wall friction and drag coefficient values are applicable for most of the modern tunnel systems since Fu-De Tunnel is also one of the state of the art tunnels.

Train induced airflow inside metro trains with ventilation shafts are studied by Yuan-dong et al. [8] through 3D numerical simulations. They compared their results with experimental results obtained from the setup prepared with exactly the same geometrical characteristics considered in simulations. For increasing the amount of flow through ventilation shafts, they placed barriers at the end of the tunnel model and saw that more air flows through ventilation ducts. They also realized that a sudden change in the direction of the air flow through the ducts is observed between the suction and discharge action of ventilation shafts.

Krasyuk et al. [9] used experimental results for verifying their analytical model for estimating train induced air flow. They found with their experimental studies that, near field effects on air flow in front of the train dampens about 35-40 times the diameter of the tunnel while the near field effects at the rear of the train continues as long as the train is in motion.

Sanz-Andres et al. [10] studied on a mathematical model for vehicle induced loads on a flat panel in order to determine the characteristics of the loads on traffic sign panels due to vehicle induced flow. They represented a force coefficient dependent on the size of the sign, the vehicle cross-section area and the distance of the sign to the middle plane of the vehicle.

As a continuation of the study mentioned above, Sanz-Andreas et al. [11] proposed a theoretical model for the vehicle-induced load on pedestrian barriers. The aim of the study was to provide simple tools for transport infrastructure community. The results are in good agreement with the tests before passing the source.

In a theoretical model based study using unsteady potential flow theory, Sanz-Andres et al. [12] also represented a force coefficient acting on the pedestrian which is induced by train movement is proportional to a single parameter which involves the pedestrian cross-section diameter, the vehicle cross-section area and the distance between the pedestrian and the vehicle.

One of the most commonly used methods to determine time dependent fluid velocity and pressure profile in closed conduits is the Method of Characteristics (MOC). MOC is a time marching numerical method applied over momentum and continuity equations to derive ordinary differential equations that govern the variation of velocity and pressure [13]. Water-hammer analysis is one of the most referenced studies utilizing MOC [14]. Air flow induced by moving vehicles can also be solved using MOC applying appropriate moving boundaries on the vehicle rear and front. Henson et al. [15] used MOC to obtain velocity and pressure distribution inside tunnels and stations by considering different draught relief shaft arrangements and obtained time dependent velocity values on station platforms and escalator tunnels. They also evaluated the effect of tunnel lining roughness height on power consumption of high speed trains. Aradag [16] used MOC to simulate vehicle induced air flow in tunnel systems and considered the effect of ventilation shafts by the use of predetermined flow percentages that are discharged or sucked through vent openings.

MOC can also be coupled with three-dimensional CFD software. For example it can be used to generate proper boundary conditions to provide the moving boundary feature to a CFD software that lacks this capability. In such a study, Ke et al. [17] used MOC based SES software together with PHOENICS code to optimize the subway environmental control system of Hsin Chuan Route of Taipei Rapid Transit System. They obtained temperature change in a station for different train speeds, considering the effect of ventilation shaft length, area and geometry. They also obtained pressure values on platform screen doors and compared their results with empirical ones. In a similar study Galindo et al. [18] used the one-dimensional gas-dynamics code OpenWAM and FLUENT together and utilized MOC to transfer data from a simplified 1D domain to a realistic 3D domain. Their main purpose was to reduce the computational cost of 3D simulations. They concluded that, proposed coupled simulation is in agreement with analytical and experimental results.

(SES software, operating on one-dimensional MOC, is considered to be one of the most reliable tools for piston effect simulations. SES is capable of simulating multiple trains travelling with non-constant velocities inside tunnels. Complicated underground systems can be modelled with it and results with acceptable accuracy can be obtained. SES owes its success to the simplification of the actual complicated, three-dimensional systems into one-dimensional models. Due to generally encountered high length-to-diameter ratios in metro tunnels, representing 3D flow structures as 1D can be managed by the use of experimentally obtained head loss coefficients. Various air flow structures like tee junctions, bends, expansions, contractions, etc. can be represented by their corresponding head loss coefficients in a one dimensional model. SES provides a wide range of possible junctions, nodes and connections. Despite of being successful in complex system modelling, its user interface is not practical for entering the data of a large metro system. For most of the time, pre-processing of SES is much longer than the simulation time.

One-dimensional MOC is not the only technique that can be used to study piston effect. Novak [19] used Fluent software with the sliding mesh option to perform 3D simulations to understand the aerodynamics of a train moving in a tunnel. He simulated a train motion with a speed of 200 km/h by considering the air flow to be compressible, unsteady and turbulent. In another 3D study Uystepruyst et al. [20] developed an Eulerian code and adopted sliding mesh technique to simulate pressure waves generated by high speed trains. Researchers also studied the piston effect by analytical and experimental means. Solazzo et al. [21] proposed a CFD modelling methodology on the contribution of wind flow and turbulence to transportation and dilution of pollutants emitted by vehicles in urban streets which are the results of both atmospheric wind and vehicular traffic. In the study explicit simulation of mechanical processes generating flow and turbulence is carried out. The results were compared with wind tunnel tests and showed a very good agreement with test results with some limitations on mean vertical velocity.

Wang et al. [22] proposed an analytical solution procedure for calculating piston effect with the incompressible flow assumption inside a straight tunnel. They compared their results with that of SES software and concluded that proposed analytical method is in agreement. Lin et al. [23] conducted experimental studies in a typical Taipei underground station and did field measurements on flow velocities inside the relief shafts. Kim and Kim [24] conducted both experiments and numerical simulations for analyzing train induced air flow in sub-ways. They constructed a 1/20 scale setup with a blockage ratio of 0.67 for a 39 meters long tunnel. There are also data driven models used for aerodynamics of railway vehicles. An example is the work of Howe [25], in which a genetic algorithm is used as an optimization tool to study high speed train motion.

In this study, an alternative approach is proposed for obtaining maximum air velocity values attained inside underground tunnels for a single train movement. The approach is to utilize neural networks, which are widely used in engineering applications where a set of data representing the theoretical background of the underlying physics is present. Many of the physical phenomena within the theory of fluid mechanics and heat transfer have already been captured by neural networks and powerful models are constructed, while no neural network solution for piston effect is presented in the literature.

1.2.2 Artificial Neural networks

ANN are data driven tools that can be used for solving most of the partial differentiable equations associated to physical phenomena. They have more generalization capability than Finite Element Methods [26]. Although there is not much effort on piston effect calculations with neural networks, there are number of neural network studies in fluid dynamics problems. In a measurement data based study, Adhikari and Jindhal [27] applied an experimental procedure to continuously record pressure drop of different non-Newtonian fluids in tube flow for neural network data generation. They stated that, neural network approach is superior to the methods that require slip correction. Kalogirou et al. [28] used multilayered neural networks with their experimental data on natural ventilation of a light weight test room. Kuan and Lien [29] used a CFD software to generate the required data for neural network training and evaluated the performance of heat sinks. They obtained reasonable agreement of neural network predicted results with those of CFD simulations. In another CFD related study, Stavrakakis et al. [30] used artificial neural networks for optimizing occupational comfort of naturally ventilated buildings by modifying the window sizes. They used CFD for data generation and used these data for neural network training. They also considered a case study through a prototype and concluded the successful prediction ability of the Radial Basis Function Network they trained. Neural networks are also used for supporting CFD studies for computational optimization. Pena et al. [31] considered the use of ANN for reducing error between different CFD approaches to various fluid dynamics problems. They simulated different cases with simplified CFD codes while they trained a neural network with laboratory tests or results of much advanced CFD models for the same cases. They used the neural network results for reducing the CFD error between the simplified models and advanced models. This way, they reduced the computational expense of CFD method in sensitivity studies. Karkoub and Elkamel [32] studied pressure distribution and load carrying capacity of gas lubricated bearings with artificial neural networks. Hu et al. [33] proposed a range dependent neural network for river flow time series prediction. By the proposed method, different neural networks are trained for different ranges of flow thus each neural network can be used for a narrower range increasing the accuracy of the networks. Pierret et al. [34] considered the two dimensional design of turbine blades using the database of the previous blade designs. They used back-propagation learning algorithm during training which propagates the error of output layer to the input layer for adjusting weights. Since back-propagation algorithm is slow in convergence, they used some improvements for speeding up the learning algorithm. They concluded that, design process is faster with their proposed method than using other Navier-Stokes solvers. They stated, more design alternatives can be considered with the proposed method in shorter times. Chen et al. [35], in their time series study using artificial neural networks, considered the interpolation of wind induced pressure values on the roof of a model low-rise building. In their study, they used the experimental data on the taps at the roof of the model and used these values for predicting pressure values at a further time interval. Although they stated the complexity of the neural network approach, they concluded that, their approach overcomes the problem of interpolation in case of a low resolution data. In another time series prediction study, Galvan-Leon et al. [36] considered use of recurrent neural networks instead of feed-forward neural networks. They compared the results of their approach with that of feed-forward networks and concluded that re-current neural network they proposed is superior especially when the prediction horizon is increased to about 4. They also stated that, for short prediction horizons, traditional models are more efficient by good prediction performances and less complexity. For most of the time, main purposes of neural network studies are to approximate or predict a relationship between input and output data. Function approximation is the most referenced study in neural network field. In such a study, Mai-Duy et al. [37, 38] proposed a method that utilizes radial basis function networks for approximating a function and its derivatives. They presented a novel method which they called Indirect Radial Basis Function Networks (IRBFN) which approximates the derivative of a function first and by integrating the solution they obtained the function itself in mathematical terms. This study has effect on capturing the mathematical background of the radial basis function networks. With results of their study they considered the application of their proposed method on Navier-Stokes equations. They considered the solution of steady, incompressible viscous flow and concluded that their approach is in good agreement with the analytical solutions.

Gölcü [39] utilized ANN approach for predicting head-flow curves of deep well pumps. He used splitter blade length, number of blades and flow rate as the input parameters and head as the target. He obtained prediction results in agreement with experimental ones. He selected number of hidden neurons in the network by a sensitivity study on the number of neurons. As performance parameters, Mean Absolute Percentage Error (MAPE), Root mean Square Error (RMSE) and Coefficient of Variation (R^2) are used in his study.

Various types of neural networks are utilized for solution of engineering problems. A problem can be solved with different types of neural networks and the one performing best can be selected as the basis of the network study. In such a study Ghorbanian et al. [40] employed different ANN for compressor performance prediction purposes. They showed that, although general regression type neural network performs best in means of mean square error, its capability is limited to interpolation. They stated that, multilayer perceptron (MLP) is a better candidate when both interpolation and extrapolation is considered.

Hayati et al. [41] used multilayer artificial neural networks for predicting convection heat transfer coefficient for a confined cylinder between parallel plates. They used experimental data for neural network training and verified their neural network results with experimental results. They stated that, neural network predicted results are in agreement with the experimental results which the trained neural networks had not seen before.

Hocevar et al. [42] in their study utilized Radial Basis Function Networks for estimating the tracer concentration in a turbulent wake. They used the values of the tracer concentration at one location as the input while the values of the same parameter, but at a further location in the trailing edge, are used as the target values. They concluded that, as the distance between the regions selected for input and target data increases, estimation capability of the network degrades. They suggested considering Reynolds and Freude Numbers as neural network parameters for improvement of the model.

Neural networks are also used for increasing the performances of other solution techniques. Manevitz et al. [43] considered time series neural networks for mesh adaptation in finite element methods used for solving time dependent partial differential equations. They used neural networks to predict the gradient and accordingly changed the mesh quality to coarse or fine when gradients are low and high respectively. They showed that, with the predicted gradient values and mesh adaptation, numerical method substantially improved.

Dibike et al. [44] employed artificial neural networks for obtaining wave equation starting with hydraulic data which is somehow different from most of the neural network applications. They wanted to use the neural network weights to obtain the differential equations that govern one and two dimensional waves. They concluded that their resulting equations are in good agreement with the actual wave equations with slight differences in their coefficients. They stated that neural networks are actually able to possess the same semantic concept with the nature when partial differential equations are assumed to represent the nature exactly.

Fadare et al. [45] proposed a neural network model for prediction of friction coefficient inside closed pipes. They used feed forward neural networks for their study and used relative roughness and Reynolds Number as input parameters. They compared their results with Colebrook's equation. Although they tried to approximate a function which is implicit in target parameter, they could obtain results in agreement with the actual values.

Another study for friction calculation is done by Bilgil and Altun [46]. They stated that, use of empirical formulae derived for open channel flow results in inaccurate predictions of flow. They used experimental data for a neural network model for prediction of friction and thus flow and showed that neural network model is a reliable tool for friction factor calculation. They compared the conventional methods and neural network results with experimental results and stated the superiority of network model. Another study on open channel flow is conducted by Sahu et al. [47] They considered a neural network prediction method for river discharge calculation. They stated that, current prediction methods for river discharge are insufficient and trained a neural network for this purpose. They considered a multilayer feed forward neural network that is trained with experimental data. They concluded that, neural network model performs better than the current prediction methods.

Rezazadeh et al. [48] in their study considered a neural network approach for predicting averaged cell voltage of Photon Exchange Membrane Fuel Cell (PEMFC) using a multi input single output neural network which is similar to the case of this study. They trained a multilayer feed forward network and compared its performance with that of a Radial Basis Function network (RBFN). They concluded that, a multilayer perceptron (MLP) performs similar to RBF while it includes much less neurons. Some researchers considered RBFN as an interpolation tool in their studies [49, 50, 51, and 52].

Sivakumar et al. [53] compared MLP performance with that of Phase-Space Reconstruction (PSR) for river flow forecasting and concluded that PSR performs considerably better than MLP for long term predictions. They attributed this result to the difference between the approximation methods of two approaches. MLP lacks good approximation with its global approximation approach while PSR considers local approximations with local neighbourhoods.

Although ANN are commonly used for solution of many industrial problems, neural networks should not be considered as tools capable of solving a complete problem. The major disadvantage of a neural network is that it needs many other tools like conventional algorithms to be used in the solution of a problem [54].

Bellman et al. [55] used artificial networks as an auxiliary tool in their optimization study for low Reynolds Number airfoils. They used genetic algorithm for shape optimization and Fluent for obtaining the results of the generated airfoil shape iteratively. They had to use an artificial neural network since the optimization procedure of genetic algorithm required large number of iterations while Fluent would take impractically long computation time. After certain amount of Fluent runs they continued with the trained network for performance evaluation.

Milano et al. [56] considered using non linear neural networks for predicting near wall turbulent flow in closed conduits. They used data generated by Direct Numerical Simulation (DNS) for neural network training. They also considered Proper Orthogonal Decomposition (POD) equivalent to a linear neural network and they compared the results of linear and non linear methods. They concluded that nonlinear neural networks performed better.

1.3 SES Software and Basics of One Dimensional Modelling

Before continuing with one dimensional modelling basics and SES software, a brief introduction to the theory of one dimensional incompressible flow is presented. For moderate train speeds where Mach number is below 0.3, incompressible flow assumption results in an accurate solution of governing fluid flow equations. Continuity and tunnel axis momentum equations need to be solved for obtaining one-dimensional velocity of air induced by an axially moving object with a known blockage ratio. Basic parameters influencing the flow characteristics are tunnel properties such as length, area and friction coefficient and train properties like drag coefficient, skin friction coefficient, frontal area, length, perimeter and speed.

Governing equations for the simplified one dimensional model, including friction and assuming infinite speed of sound are given below

$$\rho \frac{\partial \mathrm{u}}{\partial \mathrm{x}} = 0, \tag{1.1}$$

$$\frac{\partial \mathrm{u}}{\partial \mathrm{t}} + \frac{1}{\rho}\frac{\partial p}{\partial x} + \tau = 0, \tag{1.2}$$

where ρ is the constant air density, p is the air pressure, t is time and u is the one-dimensional, axial velocity. According to the first equation, even though the flow field is unsteady, velocity can adjust itself to any changes immediately in the whole flow field due to the incompressible nature of the fluid. τ represents the external frictional force exerted on the air flowing through the annulus between the train and the tunnel walls and is given in Equation (1.3) [57].

$$\tau = \frac{1}{2A_{annulus}}\left[\, f_{tunnel}\, u|u| S_{tunnel} + f_{ttrain}\,(u - V_{train})|u - V_{train}| S_{train} \,\right], \tag{1.3}$$

where f_{tunnel} and f_{train} are the friction coefficients that prevail in the annulus between the train and the tunnel. Although quite simplified when compared with non-homentropic flow that includes the effect of compressibility and does not necessarily assume equal entropy of outside and inside air, incompressible flow assumption proved to be successful in obtaining flow velocity in tunnels (Woods and Pope, 1979). Having stated the theory of one dimensional incompressible flow briefly, SES software and basics of one dimensional modelling is presented in the following section.

SES is an authoritative software developed for subway environmental simulation purposes. SES basically utilizes MOC and can be used for both simulating natural ventilation induced by moving vehicles and forced ventilation supplied by ventilation fans. Note that, SES assumes one dimensional incompressible flow with infinite speed of sound which gives reasonable results in velocity calculations. For comfort ventilation purposes, SES can be used for simulation of multiple routes, multiple vehicles and multiple subway environmental structures such as ventilation shafts, tunnels, stations, staircases, axial ventilation fans and momentum exerting jet fans on the flow field. As long as the whole underground system is intended to be simulated at a time, 3D modelling cannot be considered as a means since it is practically impossible to solve the whole underground system with any conventional CFD package. Complexity of the actual systems together with the moving boundaries of multiple trains encountered in metro operations makes it almost impossible to work within a 3D domain. On the other hand, when dimensions of the underground structures are investigated in detail, it is seen that most of the system components have a very high length to hydraulic diameter ratio which makes it possible to model the system in one dimensional domain.

Modelling an underground system in 1D requires careful reduction of dimensions into one. All three dimensional systems are approximated in one dimension successfully with the aid of major and minor head loss coefficients of the structures.

Since the flow is considered one dimensional, all flow resistances associated with the actual structures should be incorporated into the model. Basics of 1D modelling are presented in this section.

Basic component of an underground system represented by a single axial dimension is a tunnel segment which has uniform cross sectional area, roughness height and slope. As long as these parameters of a segment are not changed, a single line segment is sufficient for modelling. In case of a cross sectional area change, a new line segment should be defined and minor head loss coefficient arising from the area change should be incorporated. In Figure 1-2, schematic representation of line sections, segments and nodes are presented.

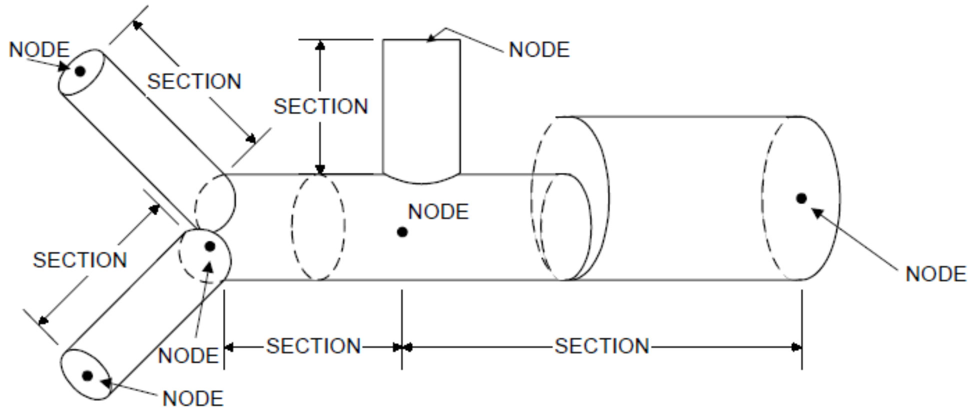


Figure 1-2 Schematics of 1D Modelling Components [58]

In Figure 1-2, one can see that, whenever flow combines or splits at any node, a new section and associated segments should be defined in order to reduce the whole 3D system into a single one dimensional flow network.

Figure 1-1 can be read in terms of metro system components as follows:

- First two angled sections; connected to each other and a 3^{rd} straight section represents two separated bores of tunnels connecting at a cross-over section. This means that, while travelling inside the metro train, a passenger will not be able to see the other track because they are separated by walls or two tunnels are completely different bores.

- Vertical section connected at the end of the first straight section corresponds to a ventilation shaft, equipped with a ventilation fan or not. Then, the larger section after the shaft section may correspond to a station section which can be much more complicated in case of an actual system.

Having identified the system components in 1D modelling, one should incorporate the corresponding head loss coefficients into the model. Minor head loss coefficients are commonly due to;

- A junction at which two angled sections meet (Angled Junction, value of the minor head loss depends on the angle of the junction)
- A junction at which two sections meet with right angle (Tee junction, value of the minor head loss coefficient depends on the aspect ratio of the sections)
- A junction at which two segments with different cross sectional areas are connected (Abrupt Area Change or Gradual Area Change, value of the minor head loss coefficient depends on the area ratio in abrupt change and angle of transition in gradual area change)
- Flow obstructions like short segments with abrupt area change or constructional details which narrow the flow passages (Square Edge Orifice in flow, depends on the ratio of orifice area and tunnel area)
- Portals to atmospheric conditions (Square Edge Orifice Entrance or Exit, value of head loss coefficient depends on the details of tunnel entrance and

exit geometry, most of the time, minor head loss for exit is taken as unity and for entrance, the value is taken as 0.34)

All minor head loss coefficients are obtained from the literature and are obtained experimentally. In SES and proposed method, these minor head loss coefficients are used. Figure 1-2 and 1-3, directly adopted from SES User Manual; present the minor head loss coefficients for different cases.

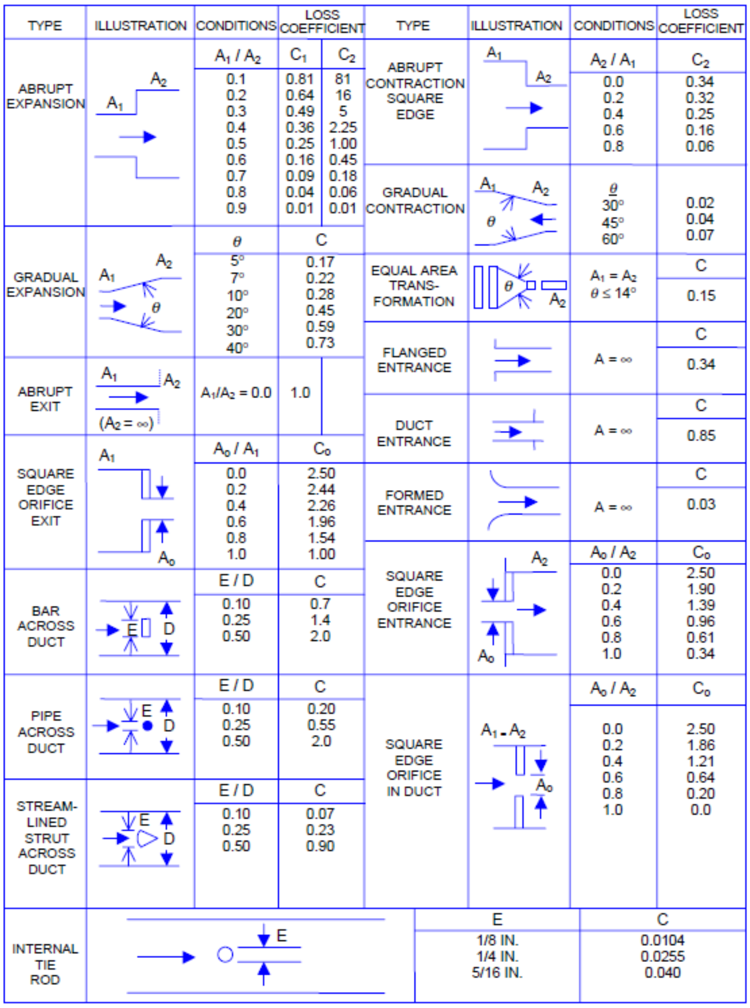
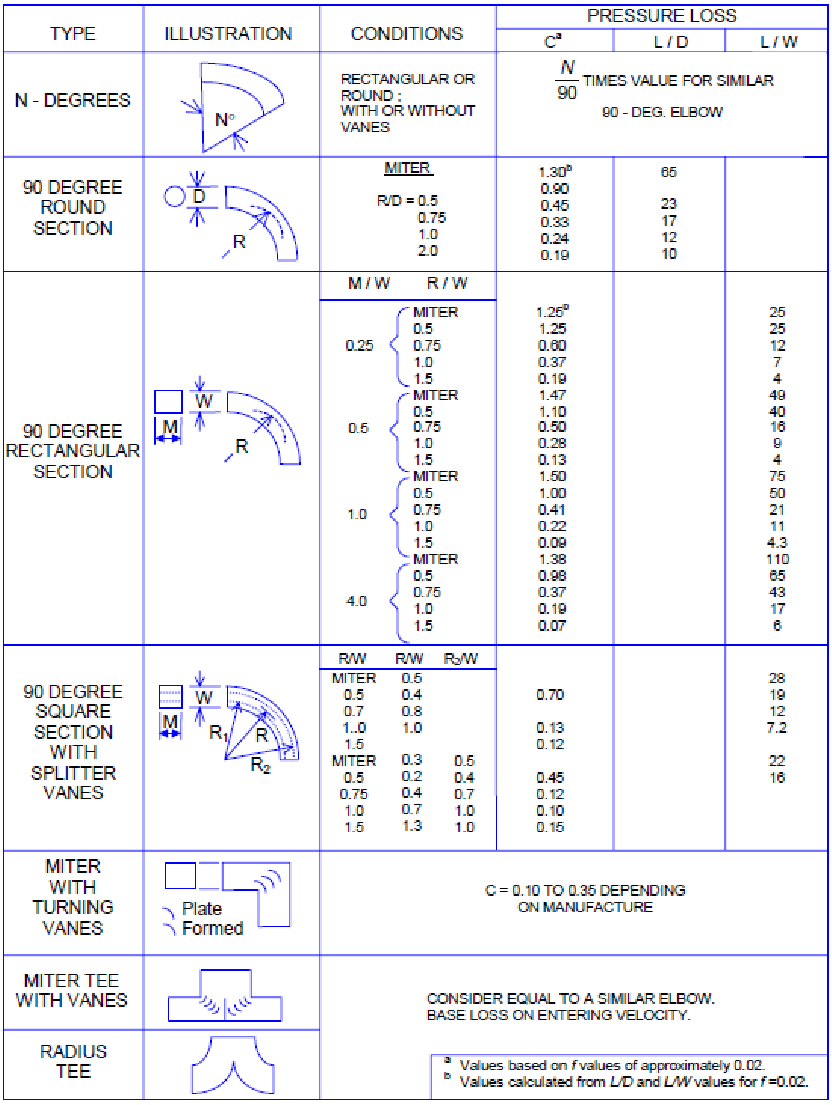


Figure 1-3 Minor Head Loss Coefficients due to Area Changes [58]



TYPE	ILLUSTRATION	CONDITIONS	PRESSURE LOSS C[a]	L / D	L / W
N - DEGREES	N°	RECTANGULAR OR ROUND ; WITH OR WITHOUT VANES	$\frac{N}{90}$ TIMES VALUE FOR SIMILAR 90 - DEG. ELBOW		
90 DEGREE ROUND SECTION	D, R	MITER	1.30[b]	65	
			0.90		
		R/D = 0.5	0.45	23	
		0.75	0.33	17	
		1.0	0.24	12	
		2.0	0.19	10	
90 DEGREE RECTANGULAR SECTION	W, M, R	M / W — R / W			
		0.25 — MITER	1.25[b]		25
		0.25 — 0.5	1.25		25
		0.25 — 0.75	0.60		12
		0.25 — 1.0	0.37		7
		0.25 — 1.5	0.19		4
		0.5 — MITER	1.47		49
		0.5 — 0.5	1.10		40
		0.5 — 0.75	0.50		16
		0.5 — 1.0	0.28		9
		0.5 — 1.5	0.13		4
		1.0 — MITER	1.50		75
		1.0 — 0.5	1.00		50
		1.0 — 0.75	0.41		21
		1.0 — 1.0	0.22		11
		1.0 — 1.5	0.09		4.3
		4.0 — MITER	1.38		110
		4.0 — 0.5	0.98		65
		4.0 — 0.75	0.37		43
		4.0 — 1.0	0.19		17
		4.0 — 1.5	0.07		6
90 DEGREE SQUARE SECTION WITH SPLITTER VANES	W, M, R_1, R, R_2	R/W — R/W — R_2/W			
		MITER — 0.5			28
		0.5 — 0.4	0.70		19
		0.7 — 0.8			12
		1..0 — 1.0	0.13		7.2
		1.5	0.12		
		MITER — 0.3 — 0.5			22
		0.5 — 0.2 — 0.4	0.45		16
		0.75 — 0.4 — 0.7	0.12		
		1.0 — 0.7 — 1.0	0.10		
		1.5 — 1.3 — 1.0	0.15		
MITER WITH TURNING VANES	Plate, Formed	C = 0.10 TO 0.35 DEPENDING ON MANUFACTURE			
MITER TEE WITH VANES		CONSIDER EQUAL TO A SIMILAR ELBOW. BASE LOSS ON ENTERING VELOCITY.			
RADIUS TEE					

[a] Values based on *f* values of approximately 0.02.
[b] Values calculated from *L/D* and *L/W* values for *f* =0.02.

Figure 1-4 Minor Head Loss Coefficients due to Bends and Elbows [58]

Reduction of a 3D structure to 1D through definitions of sections, segments and application of minor head loss coefficients is presented by a sample structure below. Note that, this structure is an extremely simple ventilation shaft which corresponds to a very minor part of an actual system. Presented structure is adopted from SES User manual and is an L-shaped ventilation shaft. In Figure 1-4, 3D view of the shaft is presented.

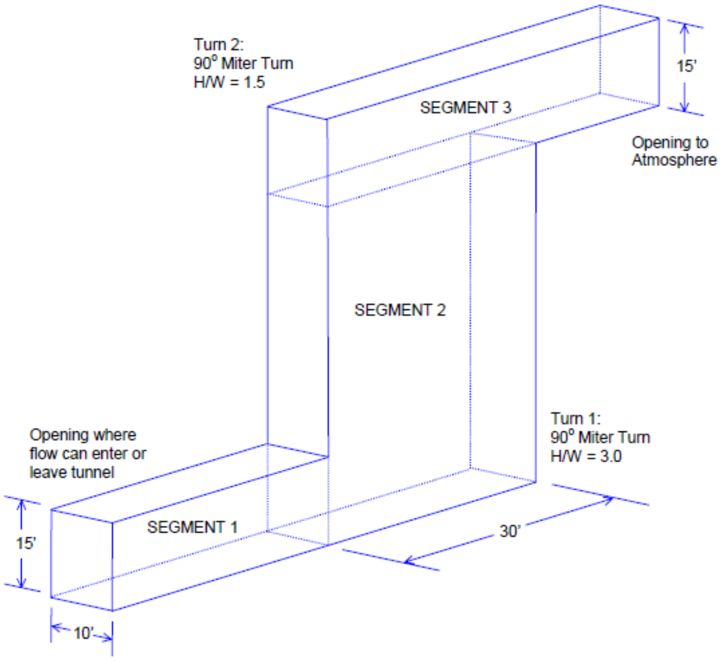


Figure 1-5 3D Shaft Model to be modelled in 1D [58]

In Table 1-1, geometric details of the shaft segments are presented. 1D modelling and application of head loss coefficients are done based on these geometric data.

Table 1-1 Geometric Details of Ventilation Shaft

	Height [m]	*Width [m]*	*Area [m]*
SEGMENT 1	4.6	3	13.9
SEGMENT 2	9.1	3	27.9
SEGMENT 3	4.6	3	13.9

When there is a sudden turn within a segment, then, head loss coefficients due to this turn should be applied both at the forward and backward boundaries of the segment. Head loss coefficients due to turns should be added to the head loss coefficients due to the area changes.

In Figure 1-5, all head loss coefficients applied to the 3 segments of the ventilation shaft are given. Note that, head loss coefficients due to area change and due to turns are presented separately.

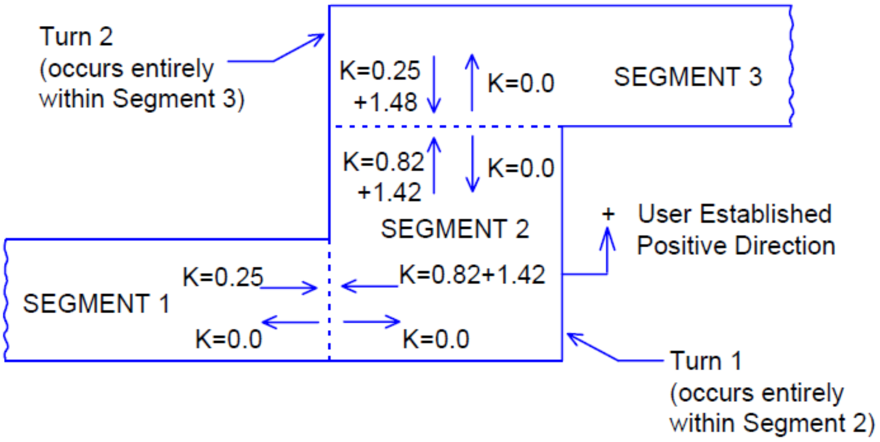


Figure 1-6 Head Loss Coefficients for the Ventilation Shaft [58]

Finally, one can represent the three dimensional ventilation shaft in a one dimensional model as seen in Figure 1-6. Note that, in one dimensional modelling, all head loss coefficients acting in the direction of flow are summed up to obtain the total head loss coefficient. One needs not to apply these coefficients at the very location of turns, bends, area changes or etc.

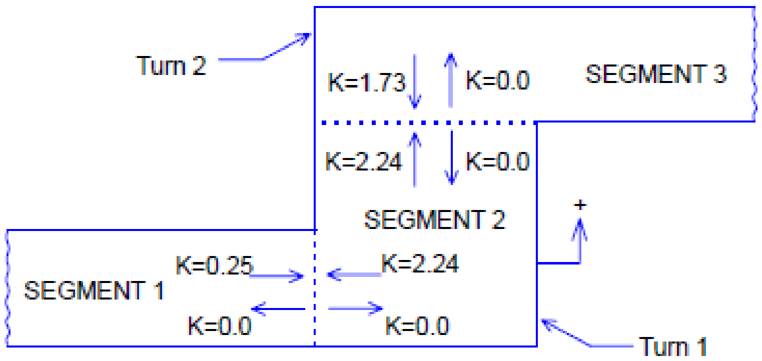


Figure 1-7 Representation of Ventilation Shaft in 1D model [58]

1.4 Motivation

Metro and road tunnels are among the most important investments of human on efficient transportation of passengers and goods. For this reason, there is huge amount of effort in design and optimization of tunnels and underground transportation systems all around the world. Before construction, simulation of designs in computer environment to check their performances is the most important stage of system design. Although hundreds of road tunnels and metro systems are designed every year, there is a short list of simulation tools that can be used during design stage. SES is one of these software tools and can be considered as a standard for most of the countries. In most of the projects in Europe and each and every project in Turkey, SES is referenced to be the simulation tool in technical specifications documents prepared by the authorities while it is not commercially available any more.

Although SES is sufficient in computational means, this software requires a huge amount of pre-processing time and data input. Because of too much time required by SES, in many projects, only a few number of alternative designs can be considered and simulated due to time constraints of the projects. To have much more time for design and optimization purposes, a simulation tool which can be configured and used for a complex system is proposed. By the proposed tool, modelling time is reduced to a much less value which enables user to change the system design within minutes and consider more number of design alternatives when compared to SES. In addition, proposed method is superior to SES when some of the technical limits of SES are considered. Although SES cannot simulate more than 75 trains at a time, proposed tool can be used for any practical number of trains in a simulation. This improvement makes the proposed tool a much better candidate to be used in road tunnel projects since hundreds of vehicles must be simulated in road tunnels. Another limitation of SES is on the drag coefficient of the vehicles. 1.5 is the maximum value that can be used in SES but in most of the tunnel projects, a sensitivity study considering different values of system parameters are required and engineers may consider much higher drag coefficients. Developed tool is also capable of using higher drag coefficient values than SES limits.

Developed tool uses artificial neural networks as the processing units and some analytical means for modelling and simulation purposes. Artificial neural networks used in this study are trained with data generated by SES software. Based on a data driven method, developed tool is also a good candidate for laboratory and field measurement studies. It is developed in such a way that, results of any test and measurement study on piston effect phenomena can be easily included into the tool through training new neural networks or modifying the weights of the current networks. Inclusion of field data would improve the performance of the neural networks.

Finally, tabulated nature of most of the international standards on safety and comfort like ASHREA, PIARC etc. makes them good candidates of neural network applications. These standards can be included into the tool for obtaining more sophisticated design software including both piston effect prediction and emission calculations. Developed tool, improved with this additional capability, will be a reliable substitute for SES.

1.5 Outline of the Thesis

In this thesis, a hybrid method utilizing artificial neural networks and analytical means is presented. Organization of the thesis is as follows;

- Success of artificial neural networks strongly depends on the characteristics of the data and the content of the data set. In order to include maximum possible knowledge about the phenomena into the model, training data set and associated variables should be selected with care. In first part of the second chapter, selection of input and target data and preparation of these data for neural network training is presented. Preparation of non-dimensional variables from the dimensional system parameters and equivalent system approach developed for non-dimensionalizing purposes is presented.

- In the second part, before training the neural network for velocity prediction, an approximate analytical solution for the problem is proposed. With the derived analytical relation between velocity ratio and non-dimensional input parameters, type of the neural network is selected to be a feed-forward since the resulting relation is an explicit expression which implies no necessity for a recurrent structure in the neural network.

- In third part of the second chapter, a neural network of type feed forward back propagation is trained with the prepared non-dimensional data. MATLAB’s Neural Network Toolbox is used for neural network training and testing. It is important to note that, neural network type is of great importance since the characteristics and governing equations of the physics involved in the theory determine the suitable network structure. Cybenko's well known theorem is referenced in this part, which is also supported by an analytical approximate solution in the 2nd section of the 2nd chapter. User is also provided with the results of training and test performances of different models namely Radial Basis Function networks (RBFN), Multivariate Adaptive Regression Splines (MARS), Polynomial Regression, and Kriging. By the comparison of the performances of alternative tools, selection of feed forward neural networks is justified.

- The essence of the thesis is basically revealed in the 3rd section of the 2nd chapter for the first time. Neural networks are strong tools for function approximation as long as there is enough data representing the actual system and the network is trained with the most general case. On the other hand, geometric nature of underground systems is so complicated that it is practically impossible to define a general underground transportation network structure. What is ideally proposed is that, a neural network would be trained for a limited domain and would still be capable of solving for a domain which is completely different from the one the network trained for. A single train inside a single tunnel is selected as the reference domain for neural network training. And with aerodynamically equivalent systems defined, trained neural network is used for solving multi-shaft tunnel systems.

- With the promising results of trained neural network together with analytical means proposed, in the 4th section of the 2nd chapter, appropriateness of the selected neural network type for the very purpose of the study is questioned. In this section, an approximate analytical solution for maximum induced air velocity inside a single tunnel is obtained. Main purpose is to check whether the analytical approximate solution meets the characteristics of the selected neural network type in terms of transfer function. It is seen that, approximate solution is an explicit relation between the selected input variables and the maximum air velocity which implies no need for a memory of neural network. Feed forward neural network is considered as appropriate for the purpose of the study.

- In 5^{th} section of the 2^{nd} chapter, an additional neural network is trained. This additional network is responsible for obtaining the time average of the air velocity. Knowledge of average velocity in addition to the maximum velocity gives more detail about the profile of the velocity. Air velocity profile in the first region within which the velocity builds up to its maximum or steady state value is assumed to be linear. This assumption together with the predicted maximum and average velocities lead to the prediction of approximate time at which the air velocity profile attains its steady state value.

- In the 6^{th} section, a brief explanation on the effect of initial velocity inside a tunnel is given. Since the neural networks are trained to predict average and maximum air velocities in tunnels with zero initial velocity, it requires accounting for the initial momentum inside the tunnel in simulations.

- In the 7^{th} section of 2^{nd} chapter, an additional neural network is trained for predicting time dependent velocity profile of air in case of train departure from the system. First, an analytic relation basically derived from the force balance on the fluid column inside the tunnel is obtained. With the obtained relation, non-dimensional friction and non-dimensional time is defined and used as neural network inputs. Trained neural network is capable of predicting air velocity for given system parameters at any instant of time within the interval of air flow dampening. Trained neural network is different than the previously trained network in such a way that it considers time as an input. Same approach, with modifications, forms the basis for simulating train stoppage inside the tunnel or a station.

- Having trained a neural network that predicts the time dependent air velocity profile in case of train departure, same neural network is used for predicting time dependent air velocity in case of train stoppage inside the system. Previously trained neural network is used without any modification in its structure but only the input data is modified to include the effect of vehicle form drag and skin friction.

- To complete the proposed model, it is necessary to include the effect of multiple trains into the model. In metro systems, there always is more than a single train so effect of multiple trains is investigated by the aid of sensitivity studies done with SES. Proposed method for multiple train simulations is presented in the 9th section of Chapter 2.

- In Chapter 3, developed tool in Simulink environment using artificial neural networks and analytical means is described in detail. All components of the simulation tool are explained with their corresponding graphical user input dialogs. A sample case is then prepared in a step by step fashion for guiding the reader throughout the modelling process. Screen captures for steps of the sample case and all necessary connections are also presented.

- In Chapter 4, all proposed methods are questioned through 3 case studies. In the first case study, applicability of the proposed method for multi-shaft tunnel systems is questioned. Obtained results proved to be in good agreement with the reference values obtained by SES. 2nd case study is for examining the model for multiple trains. 3rd and the final case study is a complete simulation of an actual metro system in Ankara. In this case, "Hastane" station is simulated with the neural network model and results are compared with field measurements and SES simulations of the same station. Results show that, proposed model can be used for very complicated underground transportation structures as a design and analysis tool.

- Finally, an overall evaluation and conclusions for the thesis and studies conducted in the thesis are presented in conclusions part. Possible further studies and extensions of this thesis are also considered in the last section.

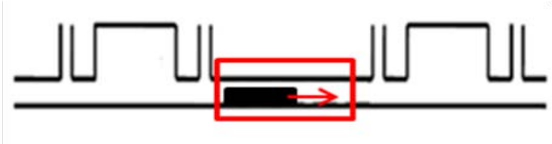
CHAPTER 2

NEURAL NETWORK MODEL

Proposed method for simulating time dependent air velocity variation in complex metro systems using neural networks starts with the simplest case of a single train in a single tunnel. Although the study aims developing a tool that can be used for complex underground systems, it is practically impossible to train a neural network for the most general underground system configuration. Underground transportation systems can vary in configuration within a very wide range of possible alternatives. For this reason, a very simple case of a single tunnel is used for neural network training. Then, using analytical means and circuit analogy of the fluid flow, trained neural networks are used for predicting air velocities in complex metro systems.

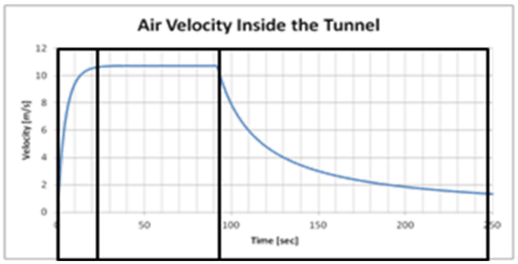
Three different neural networks are trained for approximating the time dependent velocity profile in three regions. Figure 2-1 represents the procedure followed for neural network modelling.

Multiple trains travelling inside a metro system with multiple stations, tunnels and ventilation shafts are to be simulated.



There is not a single pattern for station, tunnel and shaft configurations. So, initially, simplest case of single train inside a single tunnel is adopted.

SES simulations of single train-single tunnel case with different values of system parameters are run. Corresponding time dependent air velocity variation values are obtained.



Instead of training a single neural network for whole time domain, 3 different regions are considered. For each region, a single neural network is trained. Second region data is used for training a neural network for maximum air velocity prediction. First region is used together with second region for prediction of time average of air velocity for the first two regions. Finally, a time dependent neural network is trained for the last region which physically corresponds to the train departure or stoppage.

Figure 2-1 Neural Network Modelling Approach

2.1 Preparation of Input and Target Data for Neural Network Training

Before constructing a neural network model for a train traveling at a constant speed through a tunnel, non-dimensional groups that can be used as the input and target parameters need to be selected. Maximum air velocity, V_{air} , that will be generated in the tunnel by the train's motion is the main output. V_{air} is affected by the parameters shown in the first 10 rows of Table 2-1. Most of these parameters are geometric, such as the length, hydraulic diameter and cross-sectional area of the tunnel and the train, as well as the lateral area of the train. There is also the friction factor for the concrete wall of the tunnel, which is taken to be constant at 0.02 for low speed underground transportation. Finally there are two drag coefficients; C_D is the form drag coefficient based on the frontal area of the train and f_{train} is the skin friction coefficient based on the lateral area of the train.

In order to reduce the complexity of the problem and increase the computational efficiency of the neural network model that will be developed, five non-dimensional parameters are formed, four of which will be used as inputs and one will be the target. First input parameter is the friction head loss coefficient in the tunnel, represented by $\left(fL/D\right)_{tunnel}$. Note that, minor head loss coefficients due to abrupt and gradual area changes and entrances and exits of tunnels are also included during neural network training, but are not represented explicitly and rather included in the $\left(fL/D\right)_{tunnel}$ term. By this approach, any head loss structure in the tunnel can be introduced to the neural network during simulations without any modifications of the network. Blockage ratio, A_{train}/A_{tunnel} and $(L/D)_{train}$ are selected to be non-dimensional input parameters to represent the systems geometry. As the fourth input parameter, f_{train}, C_D, A_{train} and $A_{lateral}$ are combined into a single overall drag coefficient based on the train frontal area thorugh the relation

$C_{D\_overall} = \left(C_D A_{train} + f_{train} A_{lateral}\right) / A_{train}$. Non-dimensional speed ratio, V_{air}/V_{train} is selected to be the only target parameter.

Neural network is trained with these 4 input and a single output parameter that are all non-dimensional. Using the ratio of air speed to train speed as the target parameter instead of using these speeds as two separate parameters leads to two major advantages.

- First one is the reduced number of parameters and consistency in working with non-dimensional parameters.

- Second and the more important advantage is the fact that the speed ratio results generated by the neural network can be used for any train speed to calculate the induced air speed. It would not require any additional runs for different train speeds as long as the 4 non-dimensional input parameters are not changed.

The idea that proposes 4 non-dimensional input parameters to be sufficient for complete characterization of the train-tunnel system is questioned with a sensitivity study. A total of 9 simulations are performed with SES software to obtain the maximum velocities induced by a train moving at a speed of 40.2 m/s. As shown in Table 2-1, values of various input parameters in these 9 runs are selected so that 3 sets, each including 3 simulations with different dimensional, but equal non-dimensional input parameters are formed.

Table 2-1 Input of equivalent systems with respect to 4 non-dimensional input parameters

	EQUIVALENT SET 1			**EQUIVALENT SET 2**			**EQUIVALENT SET 3**		
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
f_{tunnel}	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
L_{tunnel}	5182	7315	3682	23165	10973	15109	366	184	259
D_{tunnel}	3.9	5.5	2.7	6.4	3.0	4.2	6.5	2.7	3.9
A_{tunnel}	15	30	7.5	41	9	17.5	29.7	7.5	15
A_{train}	7.3	14.4	3.6	16.8	3.6	7.3	14.4	3.6	7.3
D_{train}	2.7	3.8	1.9	4.1	1.9	2.7	3.8	1.9	2.7
L_{train}	21.6	30.5	15.2	30.5	14.5	19.8	61.0	30.5	43.3
$A_{lateral}$	236.7	470.1	117.8	495.8	111.7	210.6	470.1	117.8	236.7
f_{train}	0.012	0.012	0.036	0.012	0.058	0.036	0.012	0.030	0.024
C_D	0.87	0.25	1.36	0.25	0.96	0.35	0.99	0.75	0.8
	Non-dimensional parameters								
$\left(\frac{fL}{D}\right)_{tunnel}$	26.8	26.8	26.8	72.3	72.3	72.3	1.34	1.34	1.34
$\frac{A_{train}}{A_{tunnel}}$	0.5	0.5	0.5	0.4	0.4	0.4	0.5	0.5	0.5
$\left(\frac{L}{D}\right)_{train}$	7.9	7.9	7.9	7.5	7.5	7.5	15.8	15.8	15.8
$C_{D\ overall}$	1.8	1.8	1.8	1.8	1.8	1.8	1.2	1.2	1.2

SES results obtained for each case are given in Table 2-2. As seen, for each set, equivalency of non-dimensional input parameters is enough to obtain the same air-to-train speed ratio within acceptable error limits. It is possible to conclude that the proposed 4 non-dimensional input parameters are sufficient to define aerodynamically unique configurations.

Table 2-2 Results for equivalent systems with respect to 4 non-dimensional input

Equivalent Set	**1**			**2**			**3**		
Simulation No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
V_{air} (m/s)	5.9	6.1	5.9	3.2	2.9	3.1	18.4	19.8	19.5
V_{air}/V_{train}	0.147	0.152	0.147	0.080	0.072	0.077	0.457	0.492	0.482

2.2 On the Selection of Feed Forward Neural Networks

Before neural network training, type of the neural network that is appropriate for the purpose of the study is determined through an analytical approximate solution. Main idea behind the current effort is to check whether a recurrent type of neural network is necessary or a feed forward neural network can be used as the solver. Although this approximate solution does not give the numerical values of velocity ratio, it is obtained for observing the characteristics of the equation that relates the selected non-dimensional parameters to velocity ratio.

Using appropriate boundary conditions, a relation between the previously selected non dimensional numbers and velocity ratio is obtained. Since the flow is assumed to be one dimensional due to the high length to hydraulic diameter ratios encountered in metro systems, and assuming incompressible flow of air with Mach number values less than 0.3, equations (1.1) and (1.2) can be used as the governing differential equations of the flow.

In search of the maximum air velocity to train velocity ratio, with a method that utilizes maximum air velocity in Equation (1.2) and considers the instant at which the velocity profile attains its maximum value, i.e. time derivative of air velocity tends to zero, following series of derivations are obtained.

$$\left.\frac{\partial u}{\partial t}\right|_{U_{\max}} = 0, \tag{2.1}$$

With Equation (2.1), Equation (1.2) takes the form;

$$\frac{1}{\rho}\frac{\partial p}{\partial x} - \frac{1}{2A_{An}}\left[f_{tunnel}U_{\max}\left|U_{\max}\right|S_{Tun} + f_{train}\left(U_{\max} - V_{tr}\right)\left|U_{\max} - V_{tr}\right|S_{tr}\right] = 0 \ , \tag{2.2}$$

For sake of simplicity, to be expanded at the very end, some parameters are grouped and renamed with appropriate expressions.

Inverse of hydraulic diameters, $D^{'}$,are defined with respect to annular area between the train and the tunnel and are expressed as follows;

$$\left(D^{'}_{tunnel}\right)^{-1} = \left(\frac{S_{Tun}}{2A_{An}}\right), \tag{2.3}$$

$$\left(D^{'}_{train}\right)^{-1} = \left(\frac{S_{Tr}}{2A_{An}}\right), \tag{2.4}$$

In equations (2.3) and (2.4), hydraulic diameters of tunnel and train are re-defined using the parameters apparent in the governing equations. Since the main idea is to capture a relationship between the non dimensional numbers that are being subject to neural network training, definitions of hydraulic diameters do not necessarily meet the actual definition for hydraulic diameter.

With above definitions, integrating Equation (2.2) with respect to x, flow axis, pressure distribution along the tunnel axis can be obtained in terms of parameters presented in equations (2.3) and (2.4) together with unknown air velocity and known train velocity.

Integrating (2.2) with respect to x gives

$$P = \rho f_{tunnel} \frac{x}{D'_{tunnel}} U^2_{\max} - \rho f_{train} \frac{x}{D'_{train}} \left(U_{\max} - V_{tr}\right)^2 + C\,. \tag{2.5}$$

Note that, absolute value in the 3rd term in Equation (15) results in a negative sign since both the air and train velocities are in the same direction latter being greater.

Constant C is obtained substituting the inlet boundary condition of P_{atm} in Equation (2.5). Final form of the pressure distribution takes the following form

$$P = P_{atm} + \rho f_{tunnel} \frac{x}{D'_{tunnel}} U^2_{\max} - \rho f_{train} \frac{x}{D'_{train}} \left(U_{\max} - V_{tr}\right)^2. \tag{2.6}$$

Solving the problem for a single tunnel makes it possible to further apply a second boundary condition at exit. Note that, dealing with metro tunnels makes it quite independent of ambient pressure since no large stack heights of tunnels are encountered due to technical limitations of metro trains travelling on metallic wheels.

Applying exit ambient pressure of P_{atm} at exit of tunnel (i.e. $x = L_{tunnel}$), Equation (2.6) can further be simplified in selected variables.

$$0 = \rho f_{tunnel} \frac{L_{tunnel}}{D'_{tunnel}} U_{\max}^2 - \rho f_{train} \frac{L_{tunnel}}{D'_{train}} \left(U_{\max} - V_{tr}\right)^2 . \tag{2.7}$$

Before concluding the derivation, defining inverse of velocity ratio as the following:

$$\beta^{-1} = \frac{V_{tr}}{U_{\max}} . \tag{2.8}$$

And defining loss coefficients as follows;

$$K_{tun} = \rho f_{tunnel} \frac{L_{tunnel}}{D'_{tunnel}} , \tag{2.9}$$

$$K_{tr} = \rho f_{train} \frac{L_{tunnel}}{D'_{train}} . \tag{2.10}$$

Equation (2.7) can further be simplified to give equation

$$1 - \beta^{-1} = -\sqrt{\frac{K_{tun}}{K_{tr}}} . \tag{2.11}$$

Rearranging Equation (2.11) with all the predefined parameters, following relation between air velocity to train velocity ratio and non dimensional numbers can be obtained as

$$\beta = \left(1 + \sqrt{\frac{f_{tunnel} \frac{L_{tunnel}}{D'_{tunnel}}}{f_{train} \frac{L_{tunnel}}{D'_{train}}}} \right)^{-1} . \tag{2.12}$$

Note that, in Equation (2.12), tunnel length to train hydraulic diameter ratio seems to come into picture instead of train length to train hydraulic diameter ratio. But one should note that, above simplified approximate solution assumes a train length equal to that of the tunnel which results in only the skin friction of the train lateral area. Assuming a train length shorter than the tunnel length would require the inclusion of both skin friction and frontal drag coefficient of the train. Then Equation (2.12) can be expressed as the following;

$$\beta = \left(1 + \sqrt{\frac{f_{tunnel} \dfrac{L_{tunnel}}{D'_{tunnel}}}{f_{train} \dfrac{L_{train}}{D'_{train}} + C_D}} \right)^{-1} . \tag{2.13}$$

It is now better to use an overall drag coefficient instead of $f_{train} \dfrac{L_{train}}{D'_{train}} + C_D$ term in Equation (26). Note that this term is nothing but the overall drag coefficient adopted during neural network training process. Then, Equation (2.13) takes the following form.

$$\beta = \left(1 + \sqrt{\frac{f_{tunnel} \dfrac{L_{tunnel}}{D'_{train}}}{C_{D\_overall}}} \right)^{-1} . \tag{2.14}$$

Overall drag coefficient on the other hand, is dependent on the geometrical features of both tunnel and the train. It is, from the experimental studies, known that, overall drag on a vehicle travelling inside a tunnel depends on the blockage ratio, σ, of the train in tunnel and the length to hydraulic diameter of the vehicle.

From the experimentally obtained family of curves representing the relation between drag coefficients, length to diameter ratio and blockage ratio, sample figures are considered and presented in Table 2-3 and 2-4.

Table 2-3 Effect of Length to Hydraulic Diameter on Drag Coefficient for Constant Blockage Ratio of 0.7

$(L/D)_{train}$	60	30	15	5
C_D	250	140	86	45

Table 2-4 Effect of Blockage Ratio on Drag Coefficient for Length to Diameter Ratio of 60

σ	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0
C_D	250	93	37.5	18.5	10	6	4	3

Using data in Table 2-3 and 2-4, curves are fitted for L_{train} / D'_{train} and σ versus drag coefficient. Obtained plots show that, a linear relationship between length to diameter ratio and drag coefficient is observed while a 5th degree polynomial fits the data in Table 2-4 with a Coefficient of Determination (R^2) of unity. By these results, Equation (2.14) is re-expressed as in Equation (2.15).

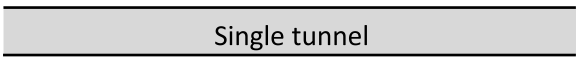
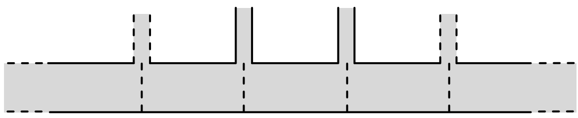
$$\beta = \left(1 + \sqrt{\frac{f_{tunnel} \frac{L_{tunnel}}{D'_{tunnel}}}{P(\sigma^5) \frac{L_{train}}{D'_{train}}}} \right)^{-1} . \tag{2.15}$$

Although exact polynomials for different length to diameter ratios are not expressed, main objective of obtaining a relation between non-dimensional groups is accomplished herein. Obtained approximate solution shows that, velocity ratio can be expressed with an explicit equation of non-dimensional input parameters not requiring an iterative solution, thus needs no memory in neural network to be selected. This derivation concludes that feed-forward neural networks, not like recurrent neural networks possessing memory, can be used for the purpose of this study.

2.3 Training Neural Network for Predicting Maximum Induced Air Velocity

To simulate a realistic underground transportation system, multiple tunnels with multiple trains, shafts, stations, etc. need to be considered. In the current effort, a simplified case with a train travelling at a constant velocity in a single tunnel without ventilation shafts is studied. Neural network trained for single tunnel then will be used for simulating any practical number of ventilation shafts and corresponding tunnels in between them. It is possible to train different neural networks for different number of ventilation shafts, but this is not practical. Instead, as seen in Table 2-5, a single neural network is trained for a simple train-tunnel configuration without any shafts. After training the neural network for a tunnel-only case it is used for cases including any number of blast shafts by defining an equivalent single train-tunnel system using simple analytical calculations.

Table 2-5 Neural Network Training and Its Capabilities

Neural network is trained with	
	A single tunnel with the following parameters Tunnel length Tunnel area Tunnel perimeter Tunnel wall friction factor
Neural network can solve maximum air velocity for	
 Multiple tunnels separated with shafts	Multiple tunnels and shafts with the following parameters Tunnel length Tunnel area Tunnel perimeter Tunnel wall friction factor Shaft length Shaft area Shaft perimeter Shaft wall friction factor

Neural network calculations are performed with MATLAB's neural network toolbox. Feed forward type neural network with a single hidden layer is selected based on the theoretical fact proposed by Cybenko [59] and the approximate analytical solution derived in the previous section of this chapter. Approximate solution shows that, velocity ratio is an explicit function of the selected non-dimensional input parameters and can be predicted by feed-forward type neural network. Number of neurons in the hidden layer can be selected using the heuristic given with the following inequality suggested by Weigend et al [60] as

$$1.1NP \leq 10NH\left[NI+1\right] \leq 3NP \tag{2.16}$$

where NP is the training sample size, NH is the number of neurons present in the hidden layer and NI is the number of neurons in the input layer, which is inherently equal to the number of input parameters. In training the neural network 400 input samples are created with SES software by using different values for the 4 non-dimensional input parameters discussed in the previous section. Input parameter values are selected carefully by considering practical upper and lower limits of dimensional parameters typically encountered in real-world applications. Using $NP = 400$ and $NI = 4$, inequality (2.16) provides the following interval for the number of hidden neurons

$$8.8 \leq NH \leq 24 \tag{2.17}$$

Different NH values in the above interval are used for training the neural network and the results are presented in Table 2-6. MSE stands for the Mean Square Error and R^2 is the Coefficient of Determination, both of which are calculated by MATLAB Neural Network Toolbox during training and with the equations 2.18 and 2.19 for test runs.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \quad , \tag{2.18}$$

where y_i is the ith observed target value, $\hat{y}_i$ is the ith predicted target, and *n* denotes the number of observations.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \right), \tag{2.19}$$

where, $\bar{y}$ is the mean response.

Table 2-6 Results of sensitivity study on number neurons in hidden layer for 400 training runs and 112 test runs

Number of neurons in hidden layer (NH)	Training runs			Test runs	
	epoch	MSE	R^2	MSE	R^2
12	122	0.0083	0.999	7.9×10^{-5}	0.988
16	53	0.0066	0.999	6.3×10^{-5}	0.991
20	71	0.0096	0.999	8.2×10^{-5}	0.989
24	179	0.0046	0.999	9.0×10^{-5}	0.987

In neural networks training, *trainbr* function of MATLAB is used which utilizes Levenberg-Marquardt optimization for updating the weights of the neural network. Training sample is divided into three groups for training, validation and testing the neural network. Percentage of data divided for training, validation and test are the default values of neural network Toolbox with the values of 70%, 15% and 15% respectively. In neural network training, early stopping, which is a method for preventing over-fitting, is also automatically applied by neural network toolbox. As the performance function MSE is used. In addition to the 400 inputs, although MATLAB Neural Network Toolbox makes test runs with a predefined percent of input data during training, an additional 112 test cases are created to test the performance of the neural network. Performance for these test runs with different number of hidden layer neurons is presented in Table 2-6. Performance parameters presented are obtained by running simulations with the trained neural network and comparing the results with those provided by SES software. After examining the results given in Table 2-6, a neural network with 16 neurons in its hidden layer is selected to be the most appropriate one and the results presented in the rest of this study are obtained with this selection.

In addition to feed forward neural networks, Radial Basis Function Neural Networks (RBFNN) with equal number of neurons with input data, Multivariate Adaptive Regression Splines (MARS), Polynomial regression and Kriging models are also considered. RBFNN with exact fit can be considered as a means for data interpolation and stated as unsuccessful for extrapolation in literature [49]. MARS is a statistical non-parametric regression model which approximates the non-linear relationship that may exist between the input variables and the target [61]. Polynomial regression is a common statistical model which approximates the relation between input and target using 2nd order terms and second order interactions of input parameters. Kriging method is also a powerful interpolation tool with a wide range of correlation functions with a disadvantage of considerable long model construction [62]. In Table 2-7, performances of feed forward network with 16 hidden neurons, RBFNN, Polynomial Regression, Kriging and MARS are presented. One can see that, feed forward network prediction possesses the best performance parameters among the considered. One should also note that, although training performance of Kriging and RBFNN models are extremely high (exact fit), their performance strongly degrade for test data which models have not seen before. This result can also be interpreted as feed forward neural networks are the best selection among the considered modelling approaches for the very purpose of this study.

Table 2-7 Comparison of Performances for Different Models

Number of neurons in hidden layer (NH)	**Training runs**		**Test runs**	
	MSE	$\mathbf{R^2}$	**MSE**	$\mathbf{R^2}$
FFNN (16 Hidden Neurons)	5.7×10^{-3}	0.999	6.3×10^{-5}	0.991
RBFN (exact fit)	1.1×10^{-21}	1	7.8×10^{-4}	0.851
MARS	3.4×10^{-4}	0.991	1.7×10^{-3}	0.673
Polynomial Regression	5.0×10^{-4}	0.980	5.8×10^{-4}	0.813
Kriging	8.5×10^{-26}	1	6.1×10^{-3}	0.389

Velocity ratio results of 112 test runs with feed forward neural network with 16 hidden neurons in comparison with the actual SES results are presented in Figure 2-1. Abscissa in Figure 2-1 corresponds to the sample number while ordinate is the velocity ratio results obtained by SES and trained neural network. One can see that, trained neural network is capable of estimating the velocity ratio for test runs that it has not seen before. It is possible to conclude that trained neural network is capable of providing acceptable velocity ratio estimates in an interval of 0.07 – 0.37, which are the practically encountered values in metro systems around the world.

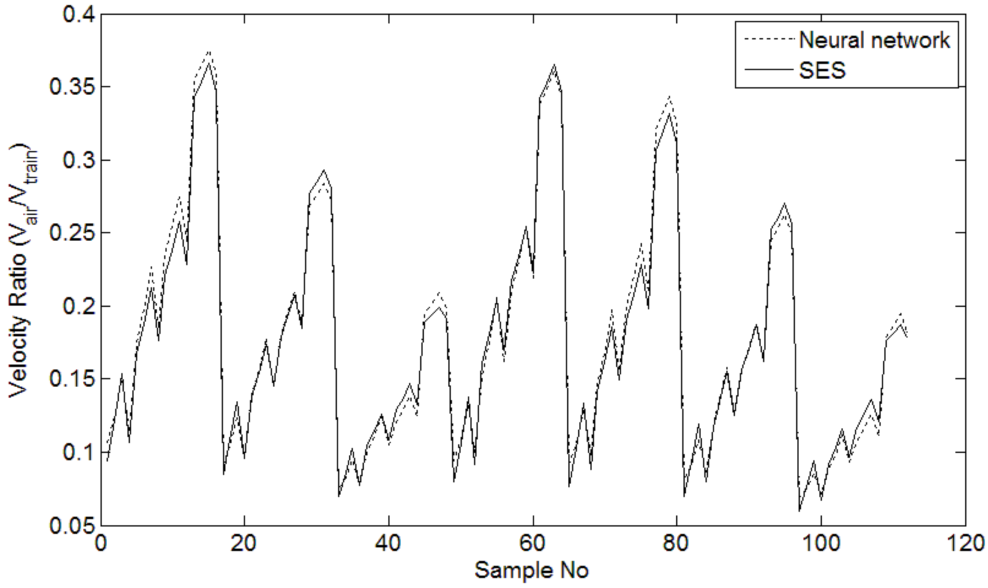


Figure 2-2 Neural network and SES results for the runs on 112 test samples

2.4 Extension of Developed Model for Complex Systems

After training and testing the neural network based on a single tunnel, developed method is extended for use in complex systems. As a starting point, the system shown in Figure 2-2 with a ventilation shaft is studied. Although the trained neural network is capable of predicting induced air velocity for a single tunnel, an approach utilizing equivalent head loss coefficients for a tunnel segment and connected ventilation shaft is proposed to obtain the maximum induced air velocity in the tunnels with ventilation shafts. For this purpose, following procedure is applied.

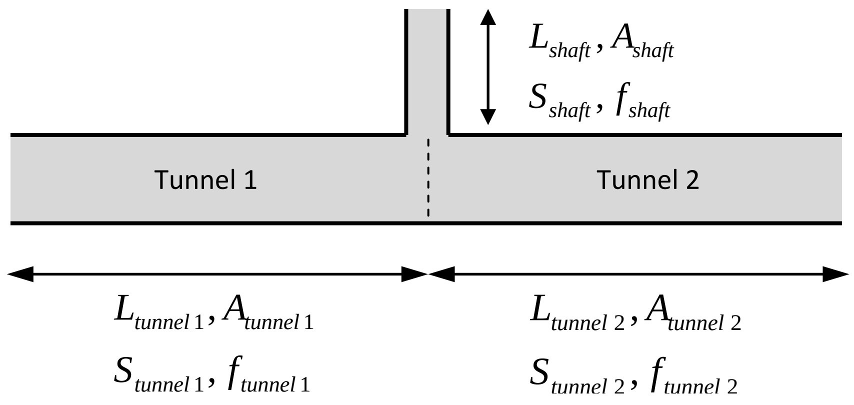


Figure 2-3 Schematics of two tunnel segments separated by a ventilation shaft

- While the train is travelling inside the first tunnel, i.e. before the shaft, an equivalent head loss coefficient is obtained for the shaft and the 2nd tunnel considering the fact that they are parallel conduits located between the same two pressure potentials. This equivalent head loss coefficient is given in Equation 2.20.

$$K = (1/A^2)\ fL/D\,. \tag{2.20}$$

A is the cross sectional area of the tunnel segment in which the train is travelling. Both the shaft and the 2nd tunnel are located between the pressure of tunnel-shaft intersection point and outside atmospheric pressure. Figure 2-3 (a) is the representation of the proposed method. Summing the equivalent head loss obtained for the part inside the red rectangle in Figure 2-3 (a) with the head loss coefficient of the first tunnel in which the train is travelling, a modified value of fL/D term is seeded to neural network instead of modifying the structure of the neural network. This approach is also extended to be used for multiple tunnels and ventilation shafts with a similar methodology.

- Same approach is applied to obtain an equivalent head loss coefficient for the 1st tunnel and the shaft while the train is travelling through the 2nd tunnel as seen in Figure 2-3 (b).

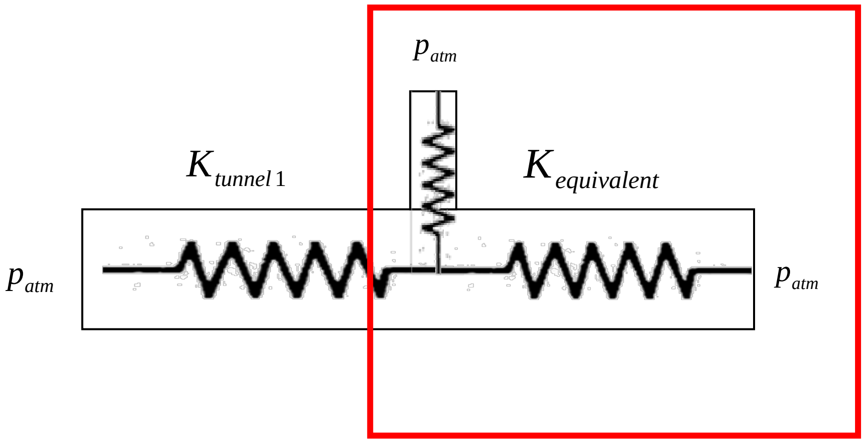
- Having obtained the equivalent head loss coefficient K_{eq} for one of the tunnels and the shaft, trained neural network is used with the sum of K values (which are the 1st non-dimensional parameter for neural network (fL/D)) of the tunnel through which the train is travelling and that of the equivalent system formed by shaft and the remaining part of the tunnel.

K value for the equivalent system represented by the region within the indicated boarders of Figure 2-3 is obtained as follows

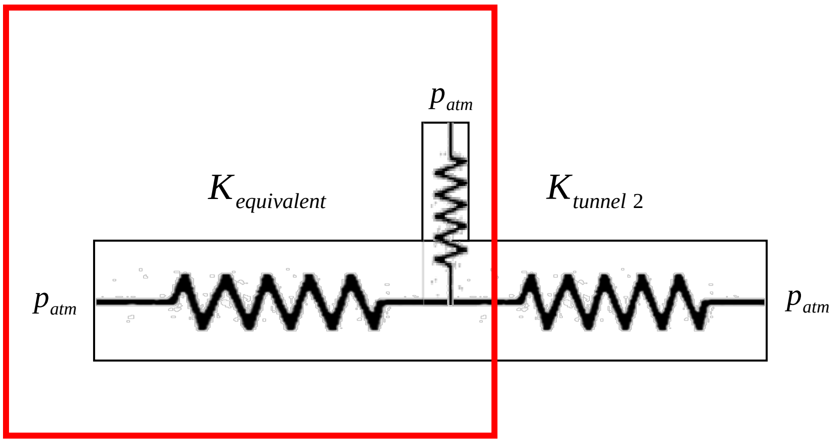
$$Q_T = Q_s + Q_t , \tag{2.21}$$

$$K_{eq} Q_T^2 = K_s Q_s^2 = K_t Q_t^2 , \tag{2.22}$$

where Q_t is the flow rate inside the 2nd tunnel when the train is travelling inside the 1st tunnel and it is the flow rate inside the 1st tunnel when the train is travelling inside the 2nd tunnel. K_s is the head loss coefficient of the shaft. K_t is the head loss coefficient for the 2nd tunnel when the train is travelling inside the 1st tunnel and it is the loss coefficient of the 1st tunnel when the train is travelling inside the 2nd tunnel. Q_T is the total flow rate inside the tunnel and shaft combination for which the equivalent loss coefficient is being calculated for. Equation (2.22) is derived using the fact that the tunnel segment without the train in it and the ventilation shaft are parallel conduits placed between the atmospheric pressure at their exit and pressure at the intersection node. Hence, head loss in the ventilation shaft is equal to the head loss in the tunnel segment that is parallel to the shaft.



(a)



(b)

Figure 2-4 Introduction of effect of ventilation shaft to the model while the train is moving inside the 1st (a) and the 2nd (b) tunnels

Equation (2.21) is used in Equation (2.22) to obtain

$$K_{eq}(Q_s + Q_t)^2 = K_s Q_s^2 = K_t Q_t^2 , \tag{2.23}$$

which is solved to obtain the following equivalent resistance

$$K_{eq} = \frac{K_s}{1 + 2\sqrt{\frac{K_s}{K_t}} + \frac{K_s}{K_t}} . \tag{2.24}$$

This approach is used for 4 different cases with parameters shown in Table 2-8.

Table 2-8 Parameters of 4 cases with ventilation shaft

		Case 1	**Case 2**	**Case 3**	**Case 4**
$L_{tunnel\ 1}$	m	950	2200	2200	950
$L_{tunnel\ 2}$	m	2200	950	2200	2200
$A_{tunnel\ 1}$	m^2	50	34	34	50
$A_{tunnel\ 2}$	m^2	34	50	34	34
L_{shaft}	m	45	45	45	45
A_{shaft}	m^2	12	12	12	12
K_{sm}	-	1	4	5	1
L_{train}	m	120	80	202	44
A_{train}	m^2	9	9	9	15
C_D for train front	-	0.14	0.44	0.14	1.1
f_{train}	-	0.023	0.023	0.023	0.023

Four cases given in Table 2-8 are simulated by the previously trained neural network combined with the equivalent head loss coefficient approach as well as the SES software. A new parameter shown as K_{sm} in this table represents minor head loss associated with the shaft. It is used to study shafts with different geometries such as contraction and expansion details or different grill structures. K_{sm} of a shaft is combined with the major head loss of the shaft to create K_s that was used in Equation (2.22). In all cases given in Table 2-8, a constant train speed of 140 km/h is used. Table 2-9 provides the results obtained. It is seen that the neural network trained for a no-shaft case can predict maximum air velocities before and after the shaft with deviations less than or equal to 10 % based on the results of SES software. It is also observed that increasing the number of shafts and making the tunnel system more complicated does not change the practicality of the proposed approach and the 10 % accuracy mentioned above does not degrade.

Table 2-9 Velocity ratio results for cases with ventilation shaft

Tunnel segment before the shaft				
	Case 1	**Case 2**	**Case 3**	**Case 4**
SES	0.107	0.174	0.206	0.169
Neural Network	0.104	0.189	0.189	0.169
% error	3	9	8	0
Tunnel segment after the shaft				
	Case 1	**Case 2**	**Case 3**	**Case 4**
SES	0.206	0.147	0.246	0.301
Neural Network	0.201	0.137	0.221	0.293
% error	2	7	10	3

Prediction capability of the Neural network Model is further questioned in 3rd chapter of the thesis. Additional runs for different configurations of tunnel systems ranging between a multiple shaft system and a complex station structure is considered in detail.

2.5 Training Neural Networks for Predicting Average Air Velocity

Trained neural network cannot be directly used for determining time dependent velocity profile since it has only the capability of deriving the maximum air velocity from the non-dimensional input parameters used for training. However, some analytical methods can help obtaining the time dependent velocity profile of the air in presence of the maximum air velocity magnitude obtained by the neural network. Different intervals of velocity profile are defined in Figure 2-4 and approximations for these intervals are explained in detail.

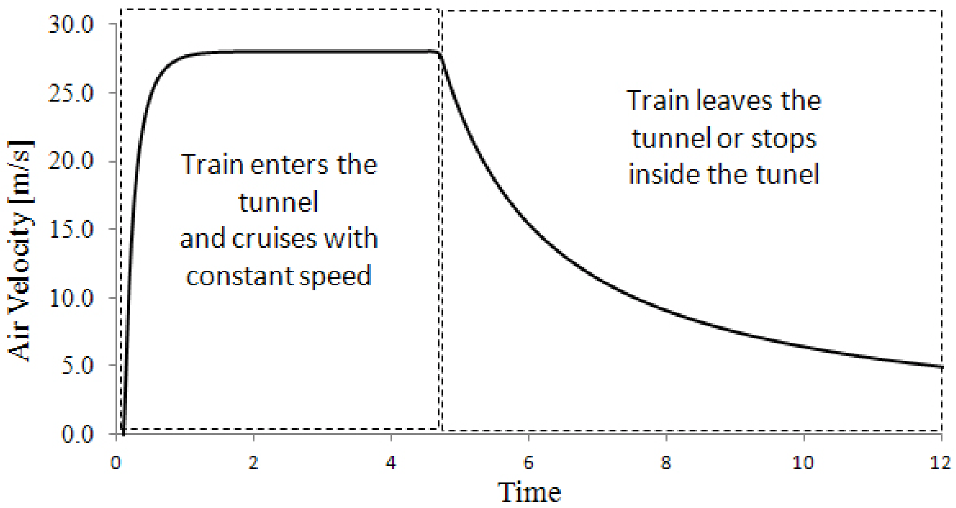


Figure 2-5 Typical Time Dependent Velocity Profile in a Tunnel

A neural network of the same characteristics with that of responsible for calculating maximum velocity is trained for obtaining average velocity of the air throughout the vehicle trip. By using the predicted average velocity, velocity profile at the 1st Region of the V-t graph in Figure 2-4 is approximated. Average velocity is used to obtain the time required for air to attain its maximum velocity, magnitude of which is predicted by the neural network. Figure 2-6 represents the proposed approach for velocity profile approximation in the 1st Region.

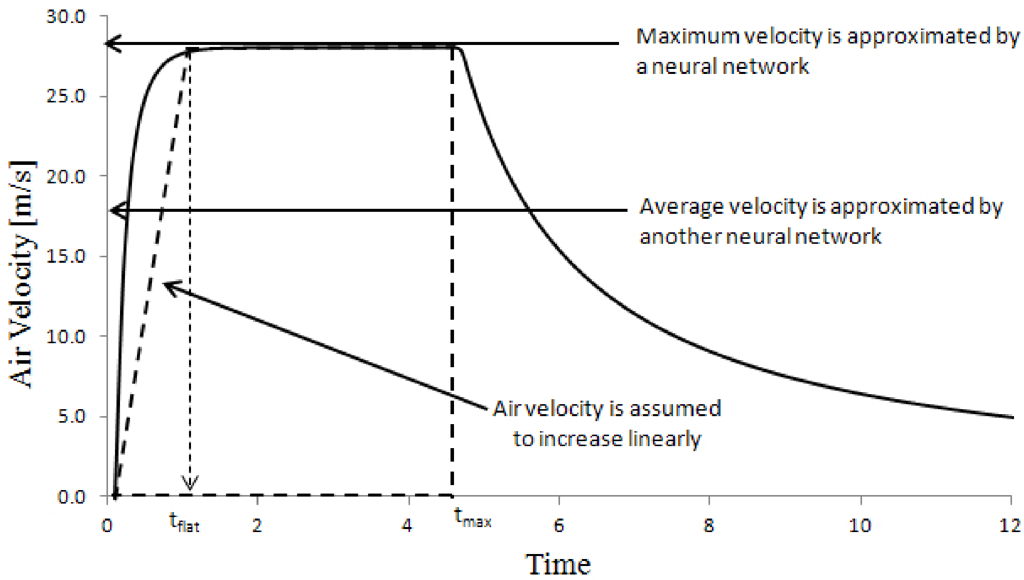


Figure 2-6 Approximation of 1st Region in Time Dependent Velocity Profile

Using Average velocity and maximum velocity together with the area under the trapezoid, time of flattening of the curve is obtained using following geometrical relation;

$$t_{flat} = 2t_{\max}\left(1 - \frac{v_{aver}}{v_{\max}}\right). \qquad (2.25)$$

Equation (2.25) can easily be obtained using geometrical relations. In Equation (2.25), t_{flat} is the time at which the velocity profile gets steady, $t_{\max}$ is the time at which the velocity is known to reach its maximum by the aid of neural network, v_{aver} is the average velocity which is also obtained using neural networks and $v_{\max}$ is again a result of neural network predicted within about %90 accuracy.

2.6 Effect of Initial Air Velocity in a Tunnel on the Induced Air Flow

Trained neural networks are capable of predicting maximum and average air velocities in case the initial air velocity inside the tunnel is zero and train enters the tunnel with a constant speed which is not always the case. When train is travelling inside a tunnel, induced air flow is split at a ventilation shaft junction, part of it flowing through the ventilation shaft while the remaining part flows into the next tunnel. To be able to predict air flow rate in the next tunnel, initial flow should be taken into account. For this purpose, superposition of initial momentum in the tunnel and the momentum induced by the train and calculated by neural network are considered. With the obtained final momentum, air flow rate in the tunnel with an initial velocity is calculated.

2.7 Time Dependent Air Velocity Profile In Case of Vehicle Departure

For predicting the time dependent air velocity profile in 2nd region, a new neural network of type feed-forward back propagation is trained with 2 non-dimensional inputs. First input is the non-dimensional friction of the system, $\left(fL/D+k\right)_{tunnel}$, and the second one is the non-dimensional time defined as $v_{\max}t/V_{Air}$. For selection of non-dimensional input parameters, an analytical approximate solution is obtained. Approximate analytical solution considers the air inside the tunnel as a rigid body and utilizes friction forces which act in the opposing direction to initial air flow.

Method basically utilizes free body diagram of the air column occupying the tunnel interior and moving with an initial speed of maximum air velocity induced by the vehicle.

Newton's Law of motion is applied over the fluid column keeping the incompressible nature of the flow;

$$-\left(k_{tunnel} + f_{tunnel}\frac{L_{tunnel}}{D_{tunnel}}\right)\rho\frac{V_{air}{}^{2}}{2}A_{tunnel} = \left(\rho A_{tunnel}L_{tunnel}\right)\frac{dV_{air}}{dt}. \qquad (2.26)$$

Integrating Equation (2.26) between initial velocity V_0 and any arbitrary velocity,

$$-(k_{tunnel} + f_{tunnel}\frac{L_{tunnel}}{D_{tunnel}})\int_{0}^{t} dt = 2L_{tunnel}\int_{v_{\max}}^{V}\frac{dV_{air}}{V_{air}{}^{2}}. \qquad (2.27)$$

Results in following for V_{air};

$$\left\{\frac{\left(k_{tunnel} + f_{tunnel}\frac{L_{tunnel}}{D_{tunnel}}\right)}{2L_{tunnel}}t + \frac{1}{v_{\max}}\right\} = \frac{1}{V_{air}}. \qquad (2.28)$$

Re-expressing Equation (2.28) in non-dimensional form, Equation (2.29) is obtained. Non-dimensional terms appearing in Equation (2.29) are used for neural network training.

$$\left\{\left(k_{tunnel} + f_{tunnel}\frac{L_{tunnel}}{D_{tunnel}}\right)\left(\frac{V_0 t}{2L_{tunnel}}\right) + 1\right\} = \frac{v_{\max}}{V_{air}}. \qquad (2.29)$$

Corresponding Non-dimensional Friction and Non-dimensional Time are defined below.

$$NDF \hat{=} k_{tunnel} + f_{tunnel} \frac{L_{tunnel}}{D_{tunnel}} \tag{2.30}$$

$$NDT \hat{=} \frac{v_{\max} t}{2L_{tunnel}} \tag{2.31}$$

where NDF and NDT are abbreviations for Non-dimensional Friction and Non-dimensional Time respectively.

There are 625 non-dimensional friction values in training data together with 7 non-dimensional time parameters making a training data set of 4375 samples. For neural network training, 4000 of the data set is used. Large number of samples results in a considerable high number of hidden neurons in a single hidden layer network so a deeper neural network with 2 hidden layers is considered. First hidden layer has 8 hidden neurons while the second hidden layer has 10 neurons in the selected neural network. Additional neural networks are trained and their performances are compared in Table 2-10. Results of the selected neural network together with SES results are presented in Figure 2-6. In Figure 2-6, abscissa corresponds to the sample number while ordinate is the velocity ratio results obtained by SES and trained neural network

Note that, although recurrent neural networks are better candidates for times series prediction, since proposed method does not provide any information about the velocity values for earlier time instants, it is impossible to use such a network. On the other hand, proposed neural network considers time variable as one of its input parameters. A total of 7 time instants are considered during training data generation. Time dependent velocity values at the instants of 20, 40, 60, 80, 100, 200 and 300th seconds of flow and at the 0th second are used in non-dimensional form as target values. Note that, for the neural network trained for time dependent dampening of air velocity, non-dimensional target velocity is defined as the ratio of maximum induced air velocity to the time dependent air velocity. Non-dimensional velocity is expressed as $v_{\max} / V_{Air}$.

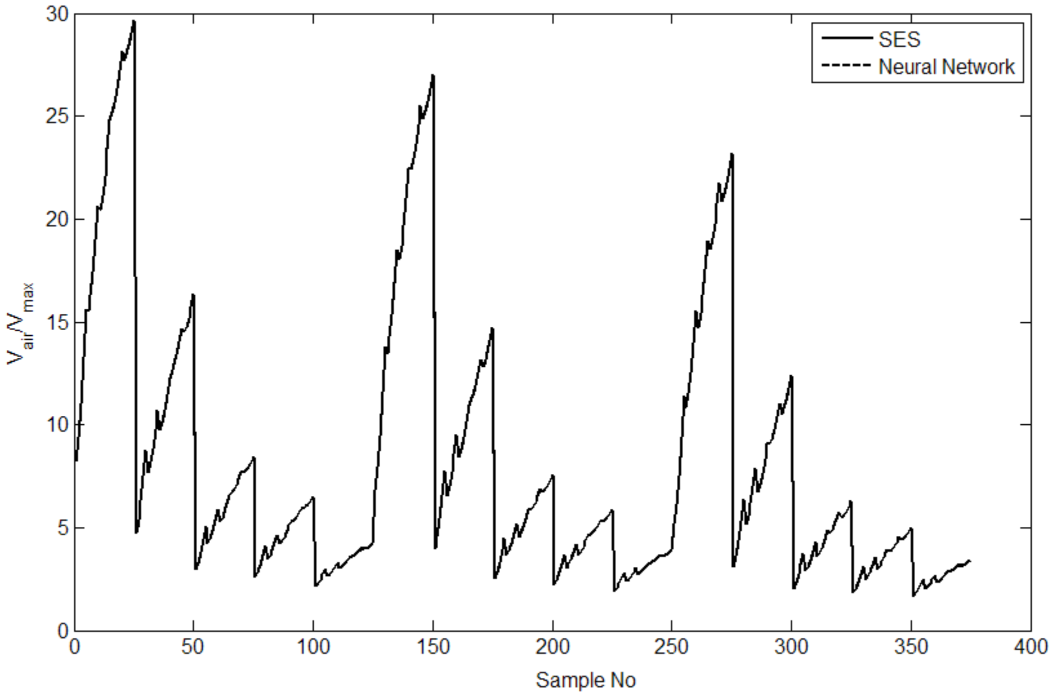


Figure 2-7 Results of Trained Neural Network for Test Cases

Obtained results with R^2 and MSE values of 0.002 and 1 respectively show that the trained neural network which considers time as one of its inputs is in agreement with SES results. Same neural network is also used for predicting time dependent air velocity in case of train stoppage. In Table 2-10, results of sensitivity study on number of hidden neurons are presented. With the obtained performance parameters, neural network with 8 and 10 neurons its hidden layers is selected because of its best level of performance. One can also refer to Table 2-11 for comparison of performances of single and two hidden layer networks.

Table 2-10 Results of Sensitivity Study on Number of Neurons in Hidden Layers for 4000 Training Runs

Number of neurons in hidden layers (NH)		**Training runs**	
1st Hidden Layer	**2nd Hidden Layer**	**MSE**	**R^2**
8	4	0.310	1
8	10	0.002	1
12	10	0.056	1
24	10	6	0.999

Table 2-11 Results of Sensitivity Study on Number of Neurons in Hidden Layer for Single Layer Network

Number of neurons in hidden layer (NH)	**Training runs**	
	MSE	**R^2**
150	15.6	0.999
200	28.1	0.999
300	6.1	0.999

2.8 Time Dependent Air Velocity Profile In Case of Vehicle Stoppage

Dampening of air velocity inside the tunnel in case of a sudden train stoppage is treated with a similar approach with that of the case train leaves the tunnel. In case of the train stoppage, on the other hand, an additional friction term, including the effect of form drag and skin friction of the vehicle is included. Rigid column of air inside the tunnel with an initial air velocity is assumed and the time dependent deceleration of air velocity under the effect of friction forces is obtained analytically.

With the addition of major and minor head loss terms due to the vehicle, Equation (2.26) takes the following form;

$$
\begin{aligned}
&-\left(k_{tunnel} + f_{tunnel}\frac{\left(L_{tunnel} - L_{train}\right)}{D}\right)\rho\frac{V_{air}^{\ 2}}{2}A_{tunnel} \qquad \ldots \\
&-\left(C_D + f_{train}\frac{L_{train}}{D_{train}}\right)\rho\frac{V_{air}^{\ 2}}{2}A_{annulus}\left(V_{air}\frac{A_{tunnel}}{A_{annulus}}\right)^2 \\
&\quad = \rho A_{tunnel}\left(L_{tunnel} - L_{train}\right)\frac{dV_{air}}{dt} + \rho\left(A_{tunnel} - A_{train}\right)L_{train}\frac{A_{tunnel}}{A_{annulus}}\frac{dV_{air}}{dt}\ .
\end{aligned}
\tag{2.32}
$$

Integrating Equation (2.32) between initial velocity $v_{\max}$ and any arbitrary velocity,

$$
\begin{aligned}
&+\left(k_{tunnel} + f_{tunnel}\frac{\left(L_{Tunnel} - L_{train}\right)}{D_{tunnel}}\right)\rho\frac{1}{2}A_{tunnel} \qquad \ldots \\
&+\left(C_D + f_{train}\frac{L_{train}}{D_{train}}\right)\rho\frac{1}{2}A_{annulus}\left(\frac{A_{tunnel}}{A_{annulus}}\right)^2\int_0^t dt = \int_{v_{\max}}^{V}\frac{dV_{air}}{V_{air}^{\ 2}}\ .
\end{aligned}
\tag{2.33}
$$

Result of Equation (2.33) is used for obtaining non-dimensional groups that should be used as input to the neural network trained for train departure. As long as the non-dimensional friction and non-dimensional time are expressed in terms of variables apparent in Equation (2.33), trained neural network is capable of predicting time dependent velocity profile of air in case of sudden train stoppage. Corresponding non-dimensional friction and non-dimensional time are defined below.

$$NDF \mathrel{\hat{=}} \frac{1}{2}\left[\left(1+k_{tunnel}+f_{tunnel}\frac{L_{tunnel}-L_{train}}{D_{tunnel}}\right)+\left(1+f_{train}\frac{L_{train}}{D_{train}}\right)\frac{A_{tunnel}}{A_{annulus}}\right] \quad (2.34)$$

and

$$NDT \mathrel{\hat{=}} \frac{v_{\max}t}{\left[\left(L_{tunnel}-L_{train}\right)+\frac{A_{tunnel}-A_{train}}{A_{annulus}}L_{train}\right]}, \quad (2.35)$$

where NDF and NDT are abbreviations for Non-dimensional Friction and Non-dimensional Time respectively.

2.9 Effect of Multiple Trains on Induced Air Velocity

Implementation of effect of multiple trains is straightforward since all input data regarding to tunnel and the train are used in non-dimensional form. To simulate any number of consecutive trains, $(L/D)_{train}$ and C_D terms are to be increased with a factor equal to the number of trains travelling inside the tunnel. In addition, since the theoretical model assumes incompressible flow of air with infinite speed of sound, headway between the consecutive trains does not alter the magnitude of maximum induced velocity. A sensitivity study on headway is done with SES Software and results of different headways are compared in magnitude of the maximum induced air velocities. Velocity vs. Time graph for different headways is presented in Figure 2-7.

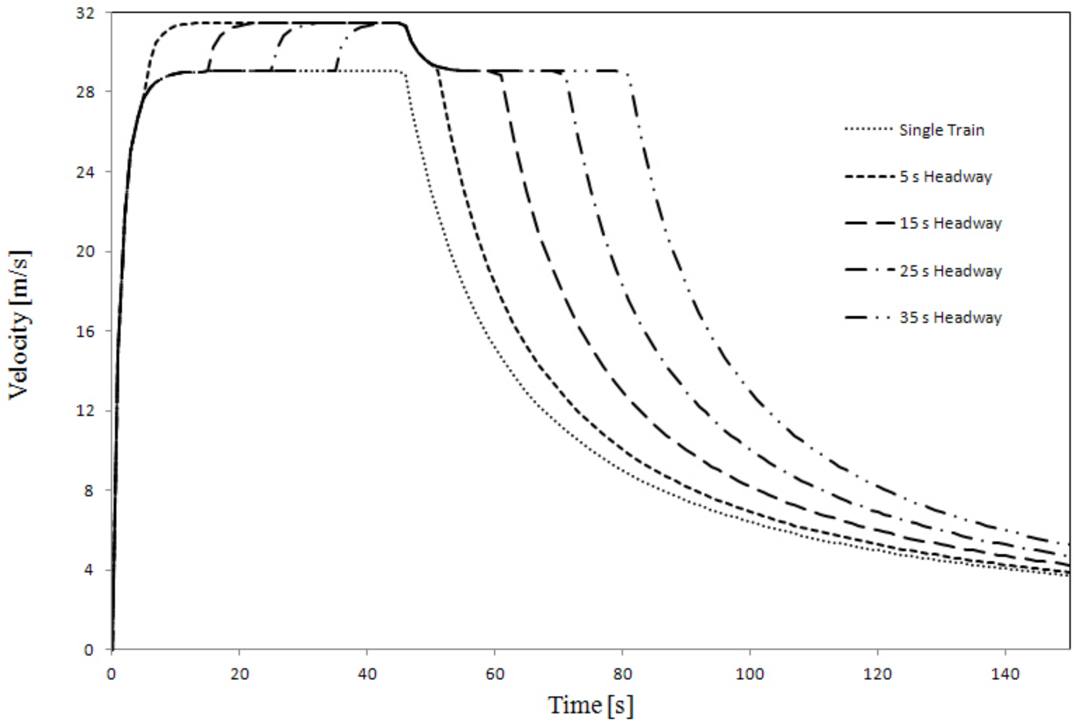


Figure 2-8 Effect of Headway on Maximum Air Velocity Induced by 2 Trains

Figure 2-8 shows that, entrance of another train into the tunnel causes a rise in the value of the maximum air velocity induced by the previous train. There is a non-linear relation between the induced air velocity and the number of trains. This relation is successfully predicted by the neural network trained for maximum air velocity.

2.10 Summary of the Modelling Approach

Neural network model for predicting time dependent air velocity variation inside complex metro systems is described with its constituents. First effort is on the preparation of the neural network training data. For introducing the metro system to a simulation model that is based the on values of the system parameters, non-dimensional parameters are formed. These non-dimensional parameters are $\left(fL/D\right)_{tunnel}$, A_{train}/A_{tunnel}, $(L/D)_{train}$ and $C_{D\_overall} = \left(C_D A_{train} + f_{train} A_{lateral}\right)/A_{train}$ which correspond to the major head loss coefficient of the tunnel, blockage ratio of the vehicle in the tunnel, aspect ratio of the train and the overall drag coefficient of the train. These parameters are obtained for a single tunnel-train couple and further means are utilized for extending the model to be used in complex system configurations. With the selected non-dimensional parameters, 3 neural networks are trained. All three neural networks are trained for a single tunnel in which a train travels with constant speed. During neural network training, for the neural networks that produce static outputs for maximum and time averaged induced air velocities, single hidden layer feed forward networks are used. Number of hidden neurons are selected using the heuristics present in the literature. On the other hand, for the neural network that is trained for predicting time dependent air velocity decay period, heuristics proposed unpractically high number of hidden neurons so a deeper network structure is adopted. For the decay period, a neural network for 2 hidden layers is trained and results proved to be as successful as the single hidden layer network.

Neural network for maximum air velocity prediction is used together with the neural network that is responsible for predicting the time average of air velocity to obtain the first two regions of velocity vs. time graph given in Figure 2-4.

Trained neural networks are used for developing a tool that can predict time dependent air velocity variation inside complex metro system. For this purpose, circuit analogy of the fluid flow is used. All the system structures except for the tunnel or station in which there is a train, are treated as parallel and series conduits depending on their relative positions. By this approach, equivalent head loss coefficients based on the flow rates are obtained for the remaining parts and these equivalent head loss coefficient are used for modifying the input of the neural networks. With the modified inputs, neural networks produced time dependent air velocity variation for the whole system instead of producing it for the single tunnel. With equivalent system approach, multiple trains can also be simulated with a similar treatment.

All neural networks and analytical means are used together for developing a simulation tool in MATLAB Simulink Environment. User can drag and drop the desired system component onto a Simulink project and can configure the system parameters through the graphical user interfaces prepared for the Simulink blocks. Details of the developed tool are presented in Chapter 3 while the capabilities of the developed tool are tested with case studies in Chapter 4.

CHAPTER 3

SIMULATION TOOL

3.1 General

A simulation tool is developed using the following basic components;

- Neural network that predicts the maximum air velocity in a single tunnel
- Neural network that predicts the average air velocity in a single tunnel
- Neural network that predicts the time dependent air velocity for train exit or stoppage in a single tunnel
- Analytical methods that consider circuit analogy for fluid flow and equivalent head loss coefficient calculations

Developed simulation tool is a Simulink library with components of train, tunnel, station and ventilation shafts. User can model and simulate an underground system within the Simulink environment using the model blocks. User can read maximum and average air velocities of air, maximum amount of induced flow rate, total head loss coefficient and time dependent air velocity during decay from the output ports of the blocks. In case further data is intended to be read, user can modify the blocks to introduce additional ports for parameters of interest. Details of blocks and the procedure for modelling a sample system are presented in this chapter.

3.2 Model Blocks

There are 5 model blocks in the developed tool. First block is the Train Block which sends information to Tunnel and Station Blocks about the trains geometrical and dynamic properties. Second block is the Tunnel Block and this is the main block for the developed tool. Station and Ventilation Shaft Blocks are inherited from this block model. Station Block is the third block and is inherited from the Tunnel Block with some modifications on the block parameters. Connection ports of a Station Block are similar to those of Tunnel Block. Ventilation Shaft Block is aerodynamically similar to Tunnel and Station Blocks while it does not utilize any neural networks but only sends information about its minor and major head loss coefficients to the system. Final block for the developed tool is the Connector Block which is not a system component but is an essential block for signal routing. Connector Block is responsible for carrying information about the system between the system components. Connector Block serves the function of extending neural networks' use to complex metro systems. Details of these blocks are presented in the following sections of this chapter.

a. Train Block

User should include a train to the Simulink model to be able to run a simulation. A train is basically the means of drag on the air column inside the tunnels and stations and defined by 2 non-dimensional parameters selected for neural network training. Although trains are defined by their non-dimensional parameter sets, user should input values of dimensional parameters regarding to the train from the user input dialogs developed in Simulink environment. In Figure 3-1, user input dialog for a train is presented.

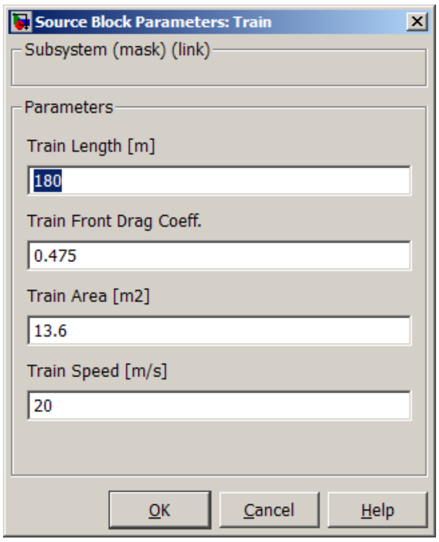


Figure 3-1 User Input Dialog for Train

User should input the length of the train, drag coefficient associated to train frontal area, train speed and frontal area of the train through the user input dialog. Train Block should be connected to all the Tunnel and Station Blocks in the model to make sure that it travels throughout the system. Train Block has only one output port to be connected to the "train input" ports of Tunnel and Station Blocks.

b. Tunnel Block

Tunnel Block is one of the main blocks of the developed simulation tool. In Tunnel Block, 3 artificial neural networks operate as the processing units. These neural networks are responsible for predicting the maximum air velocity, time average of the air velocity for the time interval within which the train is inside the tunnel and the time dependent variation of air velocity after the train leaves the tunnel system. Tunnel Block can be connected to another Tunnel Block or Station Block with or without a ventilation shaft connected to it. As long as there is not any ventilation shafts in the system, Tunnel Block can be directly connected to the following and previous tunnels and stations without using any Connector Block, which carries information of the system between the blocks. Details of the Connector Block are also described in the following sections of this chapter.

Tunnel Blocks accept signal of information about the train, head loss coefficient of the whole system behind that particular tunnel block (K from Previous Port) and head loss coefficient of the whole system after that particular block (K from Next Port) through its input ports. This information is routed and non-dimensionalized inside the block and fed into the neural networks. Non-dimensional output of the neural networks is then converted into the air velocity values using the train speed. Tunnel parameters are input by the user through the user input dialog presented in Figure 3-2.

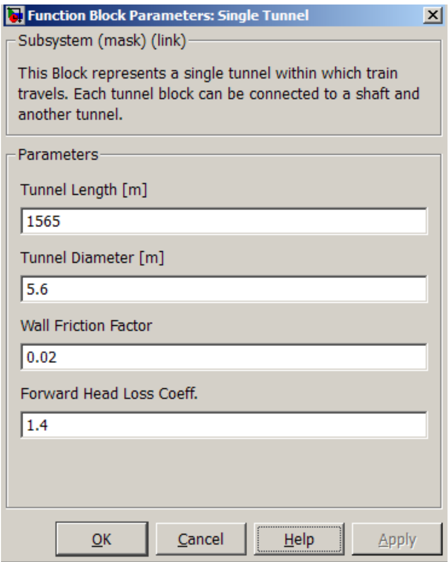


Figure 3-2 User Input Dialog for Tunnel

User should input tunnel length and hydraulic diameter together with constant head loss coefficient of the tunnel walls and forward head loss coefficient of the tunnel that can be obtained from Figure 1-2 and Figure 1-3. Although the system parameters are to be input in SI units, user can provide the software with any other unit system as long as the units are configured consistently.

c. Station Block

Station Block is another main block in the tool and is inherited from the Tunnel Block. In addition to the parameters that are similar with Tunnel Block parameters, in Station Block, user should input duration of train dwell, headway between consecutive trains and maximum allowable train speed inside the station during train entrance and exit. Station Block accepts the values of head loss coefficients of the system before and after itself through its "K_PT" and "K_NT" ports respectively. This block also accepts initial flow rate induced by the train in the previous tunnel through its "Q_0" port. It sends total head loss coefficient values through its "K to Previous" and "K to Next" Ports. In this block, there are also 3 artificial neural networks which are similar to those in Tunnel Block. Station Block can be connected to Tunnel Blocks directly as long as there is not any ventilation shaft between the tunnel and station. User can model a station with multiple staircases using Station Blocks and Ventilation Shaft Blocks together. For instance, to model a station with 2 staircases, user should use 3 Station Blocks which are separated by 2 Ventilation Shaft Blocks. One should note that, effect of concourse levels of stations can also be included into the model by introducing the total head loss coefficient of concourse level to the Ventilation Shaft Block. Station Block parameters are input through the user dialog presented in Figure 3-3.

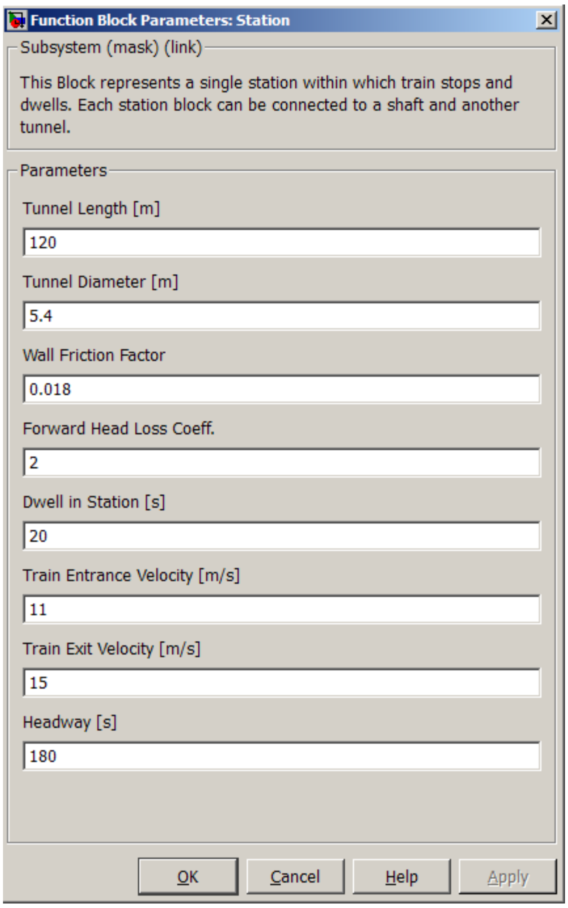


Figure 3-3 User Input Dialog for Station

d. Ventilation Shaft Block

Ventilation Shaft Block is another block which does not utilize artificial neural networks like Train Block. Ventilation Shaft Block is basically used for simulating a ventilation shaft installed in the tunnels or simulating staircases inside the stations. Ventilation Shaft Block basically calculates the total amount of flow resistance through the block itself and sends information to the model about the total flow resistance between the atmospheric exit port of the ventilation shaft and the intersection point between the shaft and the tunnel or station. Ventilation Shaft Block accepts input data from the user input dialog presented in Figure 3-4.

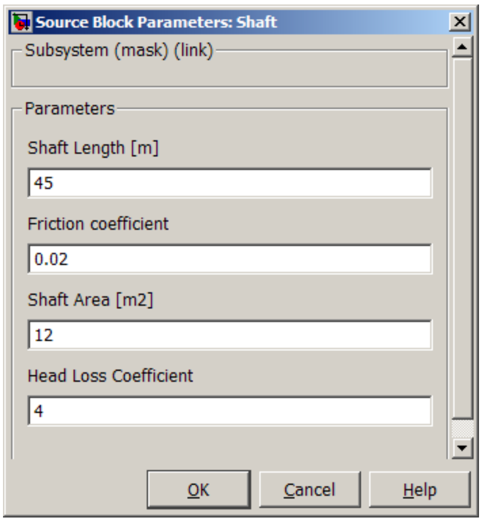


Figure 3-4 User Input Dialog for Ventilation Shafts and Stairs

a. Connector Block

Connector Block is used for carrying information between shaft-tunnel or shaft-station interface. When user includes a ventilation shaft at any location, then this ventilation shaft should be a used together with 2 connector blocks. First connector block is used for sending information about all the tunnels, stations and shafts located after that location to the previous tunnel or station and the second one is used for sending information about all tunnels, stations and shafts before that location to the next tunnel or station. Connector Block uses its “K_Sh”, “K_Tun”, “Q_NT”, “fL/D, A(NT)” and “fL/D, A(NT)” ports for carrying information between ventilation shaft and connected tunnels and station. Connector Block is the implementation of analytical method which is proposed for extending the use trained artificial neural networks to complex underground systems. In the next section of this chapter, guidelines for using the developed tool are presented through a sample tunnel-shaft-station system.

3.3 Modelling Tutorial

In this section, user guidelines for the developed tool are presented through a sample case study in which a metro station of a light rail transit system (LRTS) with connecting tunnel on the left side is considered. This sample case considers that vehicle leaves the system from the right hand side of the station through open tracks. A ventilation shaft is installed on the left hand side of the station for piston effect reduction. Modelling and simulation is described in a step by step fashion.

3.4 Overview of the Problem to be Solved

A tunnel-shaft-station model shown in Figure 3-5 is considered for the sample case. Train enters the tunnel system from the left portal of the tunnel with a constant speed of 20 m/s and enters the station with a decreased velocity of 8 m/s. After vehicle stops at the platform level for detraining and entraining of passengers, it restarts its motion after 20 seconds. Maximum train velocity at the exit of the station is set to 8 m/s. Geometrical data about the system components are given in Table 3-1 and Train data is presented in Table 3-2.

Table 3-1 Geometrical Properties of the LRTS

	TUNNEL	STATION
Length [m]	900	120
Area [m^2]	21	100
Perimeter [m]	18.4	40
Friction Coefficient	0.03	0.01
Minor Head Loss Coefficient	0.98	1

Table 3-2 Properties of the Train

Train Length [m]	120
Train Frontal Area [m^2]	18
Train Frontal Drag Coefficient	0.75
Train Skin Friction Coefficient	0.023

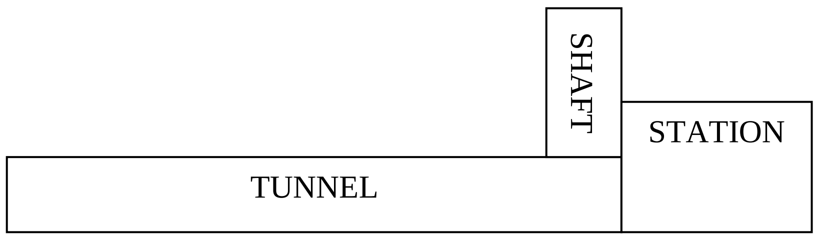


Figure 3-5 Schematic Representation of the Sample Case

Preparation of the Simulink model for the case study using the developed model library is described below.

- Place the Model Library named "PISTON" in the working directory of MATLAB. Note that model library can be used only if Simulink is installed together with MATLAB Software.

- Start Simulink and create a new empty model.
- Launch the model library called “PISTON”. Model library includes all model blocks of tunnel, station, train, ventilation shaft and connector together with some of the most commonly used Simulink blocks. Screen shot of the library is given in Figure 3-6.
- Drag a single tunnel, station, train and ventilation block into the created empty model. Also drag and drop 2 connector blocks to be used for connecting tunnel, shaft and station to each other. (see Figure 3-8)

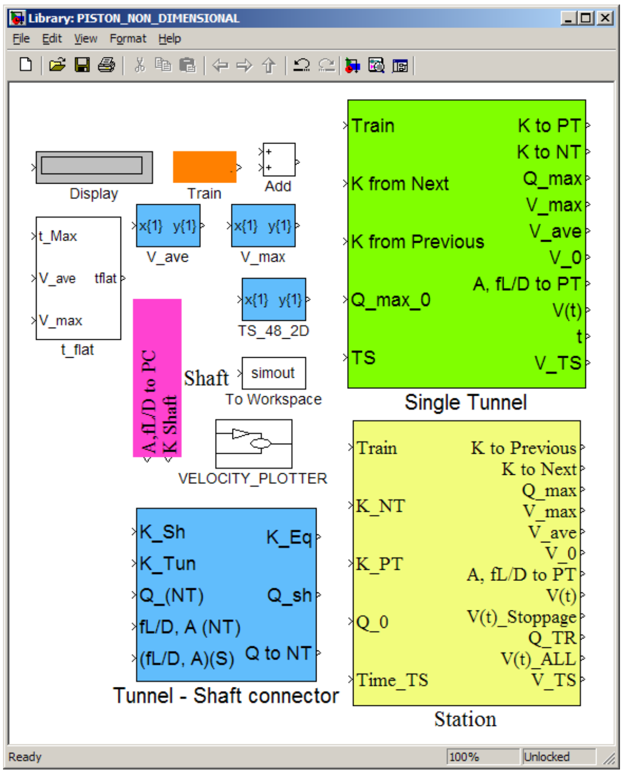


Figure 3-6 PISTON Model Library

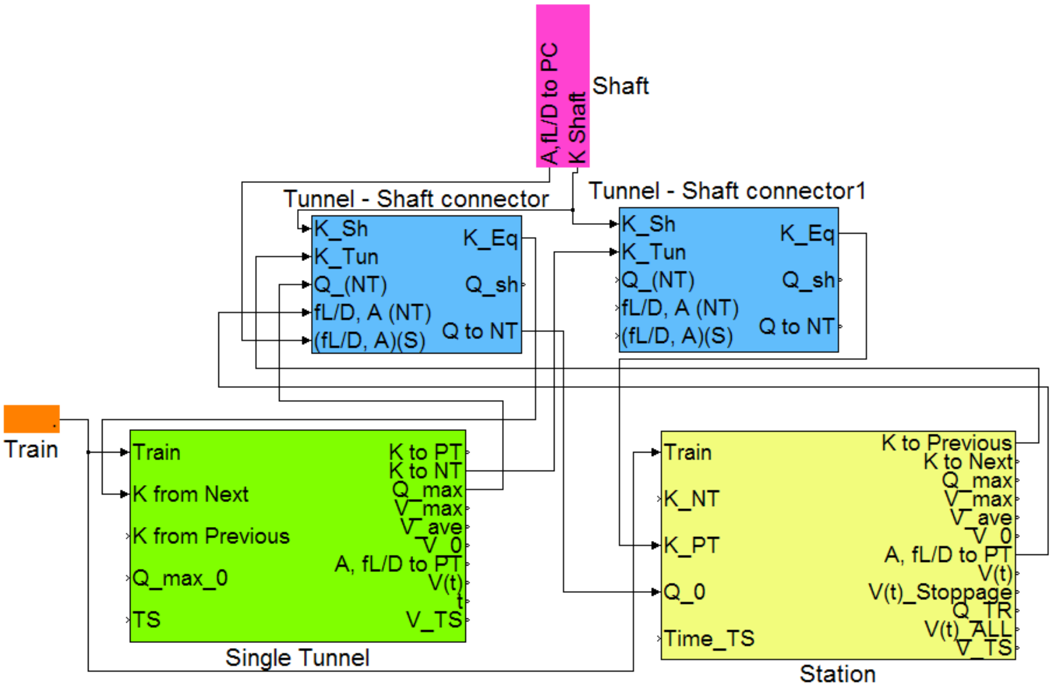


Figure 3-7 Components for the Sample Case

- User should connect the blocks through their proper connection ports. Although there are a number of input and output ports, not all of the ports have to be connected. Some of the ports are only reserved for monitoring some important variables and are not necessarily be connected during simulation. Mandatory ports and connections are presented for each pair of blocks in Figure 3-8 to Figure 3-13.

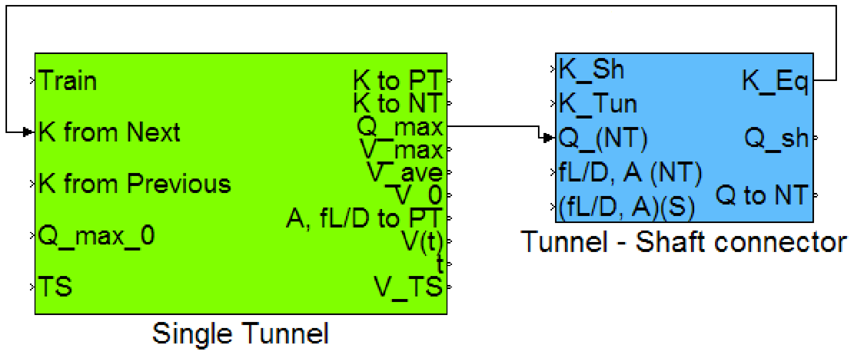


Figure 3-8 Connection of Tunnel and First Connector Block

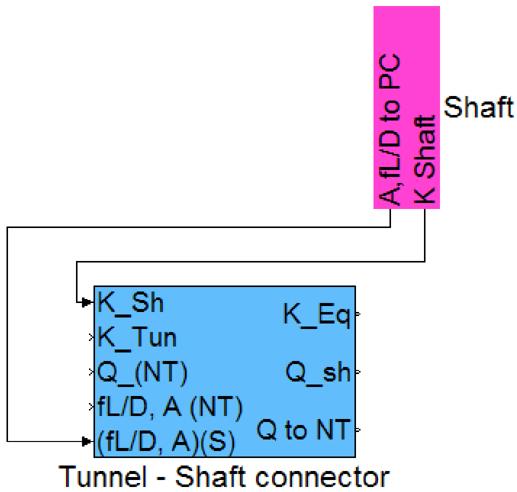


Figure 3-9 Connection of Shaft and First Connector Block

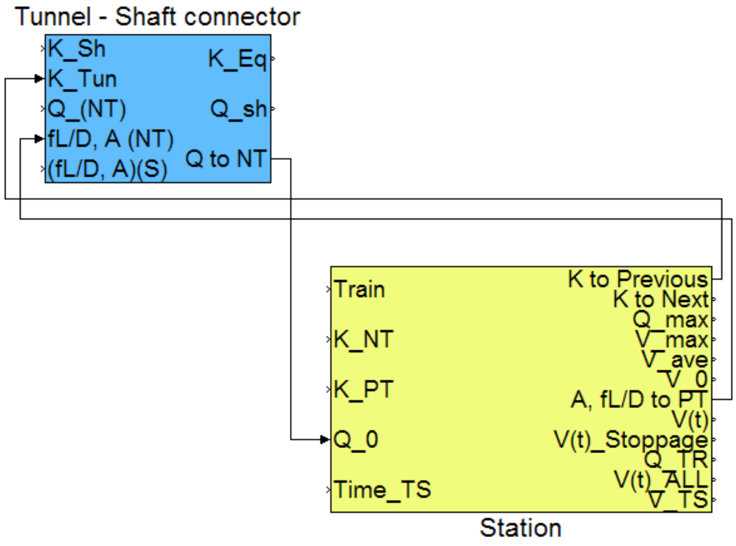


Figure 3-10 Connection of First Connector Block and Station

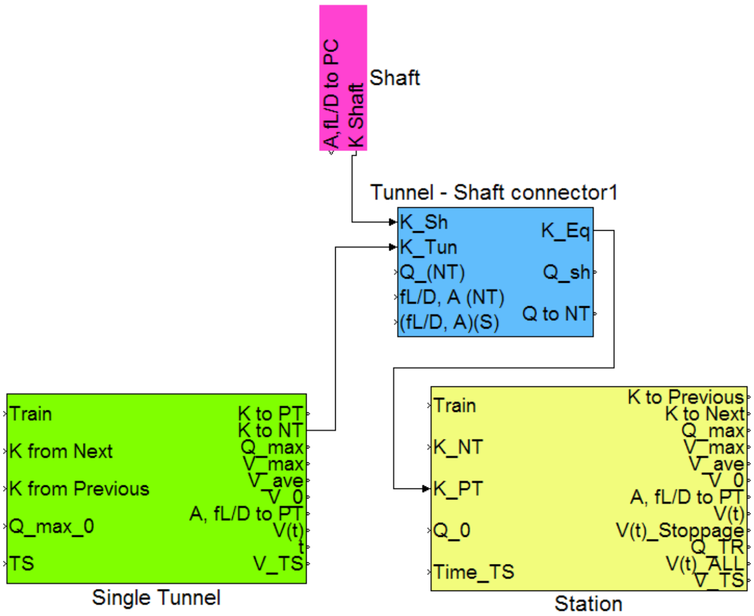


Figure 3-11 All Connections of the Second Connector Block

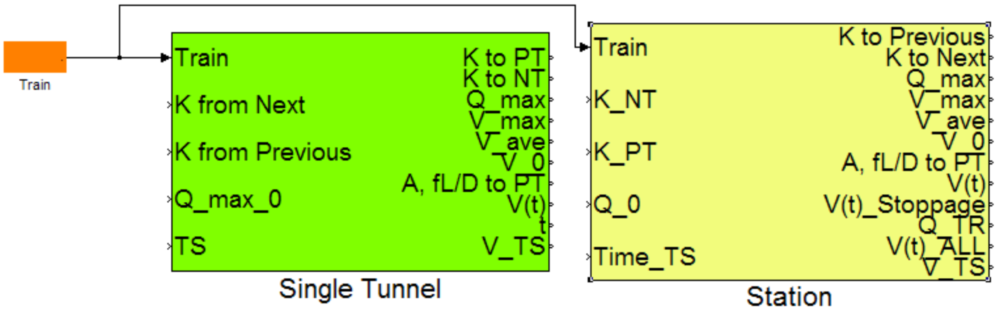


Figure 3-12 Connections of Train

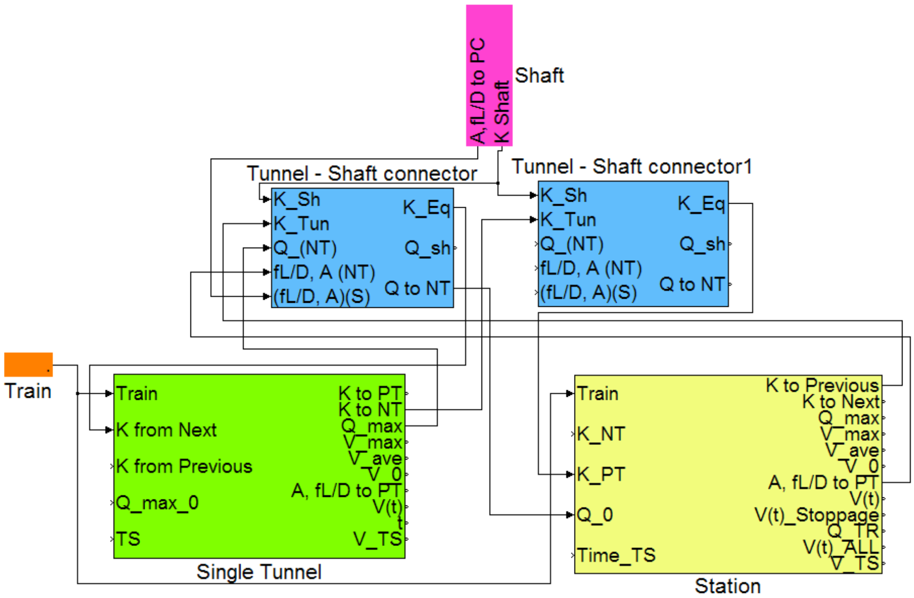


Figure 3-13 Whole System Model for Sample Case

1. After the model is prepared, run the model and the results of time dependent air velocity values are recorded in MATLAB workspace. User can use these results for plotting options within MATLAB or can use a

spreadsheet application for data processing and plotting purposes. Obtained results for the case study are presented in Figure 3-14.

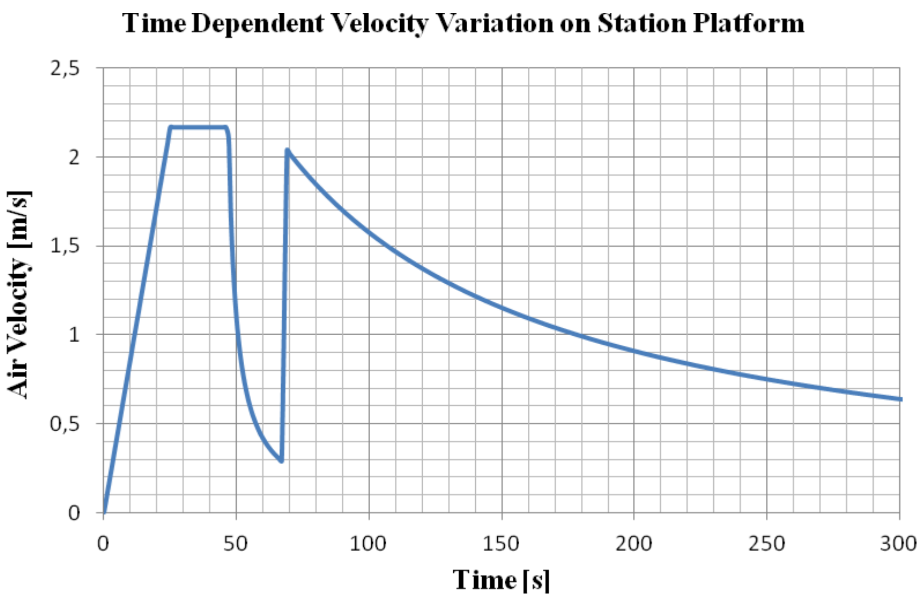


Figure 3-14 Results of the Sample Case

Model block for any component can be modified when additional features are intended to be included. Additional neural networks, responsible for predicting time dependent pressure variation, time dependent drag force on the train or other parameters of interest can be included to the model easily since the tool is developed in such a way that user can insert a neural network directly in to the blocks without any additional effort.

CHAPTER 4

CASE STUDIES

Developed simulation tool which uses neural networks and analytical methods are tested through case studies. 3 case studies, each questioning different capabilities of the developed tool are considered. In the 1st case study, simulation model is used for simulation of a tunnel system equipped with 2 ventilation shafts. In the 2nd case, multiple vehicles travelling with a predefined headway are simulated. In the 3rd and final case study, all capabilities of the developed simulation tool are tested through simulation of an actual metro station. Results obtained with the proposed method are compared with field measurements. In Table 4-1, details of 3 case studies are summarized.

Table 4-1 Summary of Case Studies

	Case 1	Case 2	Case 3
DESCRIPTION	Proposed method is tested for a configuration of tunnel-shaft-tunnel-shaft-tunnel. All deflection points on the velocity vs. time graph, corresponding to train crossing from the shaft portals are obtained. Results of proposed method are compared with SES Software results.	Proposed method is tested for 2 and 3 consecutive train conditions. In both conditions the tunnel system is composed of 2 tunnels and a ventilation shaft located at the intersection of these tunnels. Maximum and time average air velocities induced by multiple trains are obtained for both 2 and 3 train conditions. Results are presented in comparison with SES results.	A complex metro station together with its connecting tunnels is simulated using the proposed method. Time dependent velocity variation of the air at the narrowest region of the station is obtained. Results are compared with SES Software results and field measurement data of the station.
OUTPUT	Graphical results of velocity values in comparison with SES	Tabulated results of maximum and average velocity values in comparison with SES	Graphical results of time dependent velocity variation of air in comparison with SES

4.1 Prediction of Deflection Points of Velocity in a Multi-Shaft System

The proposed method is tested for a tunnel system of 2250 meters total length with 2 equally spaced identical vent shafts as shown in Figure 4-1. Tables 4-2 and 4-3 provide the tunnel and train related data of this case. Following is a summary of what happens as the train is moving in this tunnel.

- At t=0 a train with a constant speed of 40 m/s enters the first tunnel from the left portal.
- At about t=19 seconds, the train reaches the 1st shaft intersection, causing the maximum air velocity in the 1st tunnel. In the meantime, air flow occurs in the 2nd and 3rd tunnels.
- At about t=38 seconds, the train arrives at the 2nd shaft intersection causing the maximum air velocity in the 2nd tunnel. At this point, there is also air flow both in 1st and 3rd tunnels.
- At about t=57 seconds, train leaves the tunnel system, inducing the maximum air velocity in the 3rd tunnel.
- Train has a length of 44 meters, which corresponds to about 1 second for complete passage of it from the inlet and exit portals and this 1 second interval is not considered in this study.

To understand the problem better, time dependent velocity variation in the 2nd tunnel predicted by the SES software is given in Figure 4-2. It is important to note that in this study the neural network is trained only to determine the maximum air velocities induced in the tunnels, which are shown in Figure 4-2.

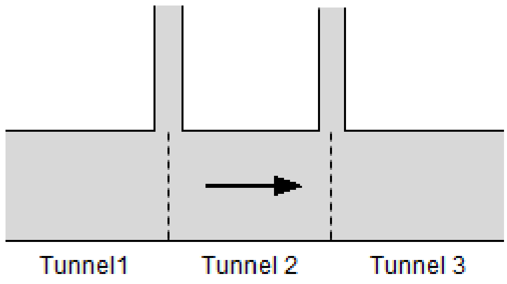


Figure 4-1 Schematics of the simulated case

Table 4-2 Tunnel and Shaft Data for the Simulated Case

	Tunnel 1	Shaft 1	Tunnel 2	Shaft 2	Tunnel 3
Length [m]	750	45	750	45	750
Area [m^2]	22	12	22	12	22
Minor Head Loss Coefficient	0.34	3	0	3	1
Friction Factor	0.02	0.02	0.02	0.02	0.02

Table 4-3 Train Data for the Simulated Case

Train Length [m]	44
Train Frontal Area [m^2]	12
Train Speed [m/s]	40
Skin Friction Coefficient	0.023
Frontal Drag Coefficient	1.1

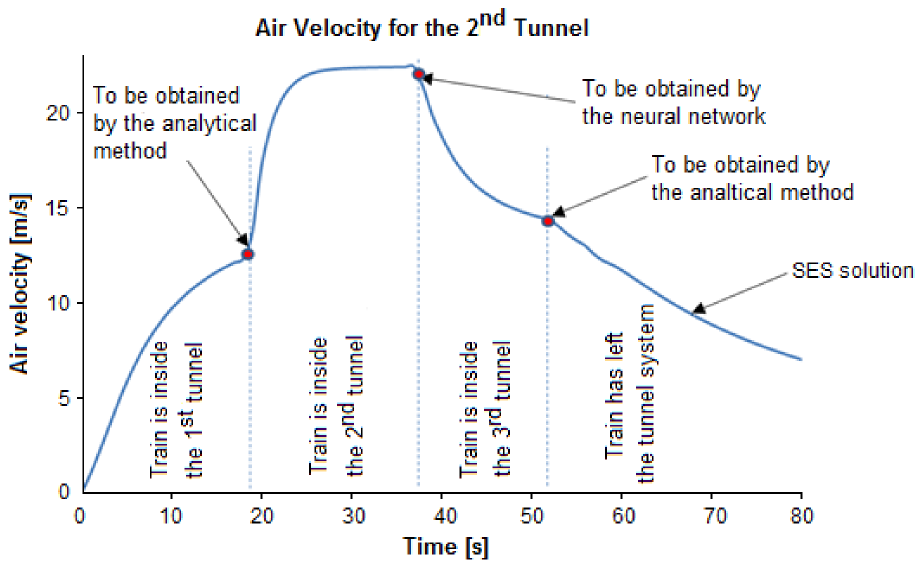


Figure 4-2 Instants of Time Dependent Velocity Profile

Neural Network simulation results for maximum velocities in comparison with SES results are presented in Figure 4-3 with the corresponding percent errors given in Table 4-4. As seen, the effect of the train movement in the furthest tunnel (i.e. air velocity in the 3rd tunnel while the train is in the 1st tunnel and air velocity in the 1st tunnel while the vehicle is in the 3rd tunnel) can be predicted with the least accuracy. This result is attributed to the possibility that SES uses friction and minor head loss coefficients dependent of the Reynolds numbers while the current study considers friction and head loss coefficient to be constant. On the other hand, air velocity in a tunnel, while the vehicle is in that particular tunnel, is obtained by the neural network in agreement with SES software. Here it is important to note that; user manual of SES software itself claims to predict air velocities with an accuracy of 10%.

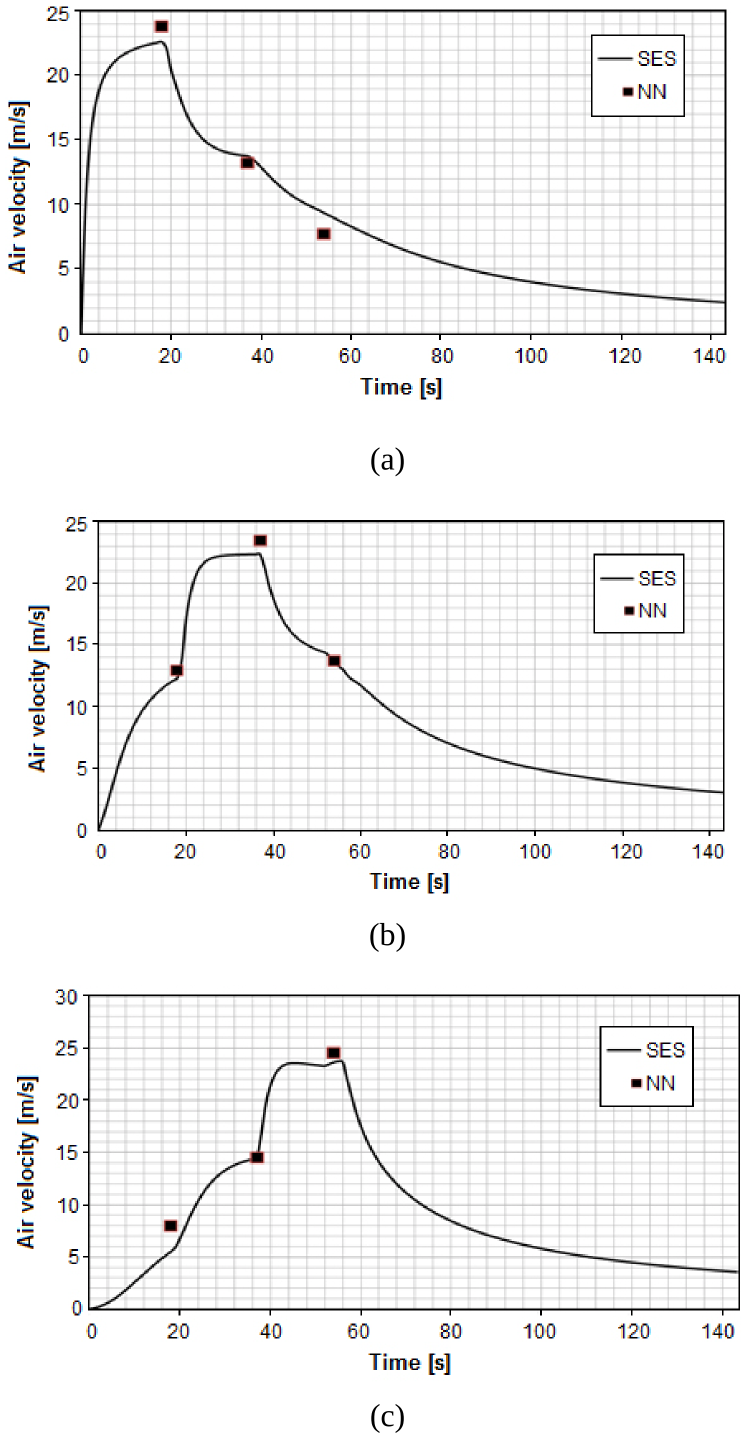


Figure 4-3 SES Results for air velocity in 1st (a), 2nd (b) and 3rd (c) tunnels and the maximum values predicted by the proposed technique

Table 4-4 Percent Error in Maximum Air Velocity

	% Error In Maximum Air Velocity		
Instant	Tunnel 1	Tunnel 2	Tunnel 3
Train leaves the 1st tunnel	5.3	5.2	**17.6**
Train leaves the 2nd tunnel	4.2	4.8	0.0
Train leaves the 3rd tunnel	**18.1**	0.9	3.5

Following are the important conclusions that can be derived from this study

- Maximum air velocity induced by the moving vehicles inside the tunnel, while the vehicle is inside that particular tunnel, can be obtained by the proposed method in agreement with the SES software.

- Although trained for a single tunnel, with the proposed equivalent system approach, trained neural network can also be used to solve a multi tunnel-shaft configuration.

- In Table 4-4, it can be seen that, 3rd column of the 1st row and 1st column of the 3rd row corresponds to the effect of the moving vehicle inside a tunnel on the furthermost tunnel segment and the error in results predicted are greater than the proposed maximum error of about 10%. These values are not directly the results of the neural networks but are calculated by analytical means assuming constant friction factor. On the other hand, SES uses friction factor dependent on the Reynolds Number and thus the total friction factor changes as the velocity increases until it attains its constant value. As a further development of the model, an analytical model that iteratively calculates the total head loss coefficient of the system components like shafts and tunnels can be considered as a future study.

4.2 Prediction of Maximum Air Velocity Induced by Multiple Trains

In this study, proposed method is tested for multiple trains travelling inside a tunnel system at the same time. Same tunnel system composed of 2 tunnels and a ventilation shaft in between is considered for 2 different train conditions. In first train condition, 2 trains with headway of 10 seconds are simulated. In the second condition, 3 trains with headway of 10 seconds are simulated and maximum and average air velocities induced by these trains are obtained. Maximum and average velocity results are presented in Table 4-5 and Table 4-6.

Table 4-5 Maximum Air Velocity Results - Multiple Trains

Tunnel 1 (before the shaft)		
	Condition 1 (2 Trains)	Condition 2 (3Trains)
SES	9.7	11.4
Neural Network	9.1	10.4
% error	6	9
Tunnel 2 (after the shaft)		
	Condition 1 (2 Trains)	Condition 2 (3Trains)
SES	8.3	9.4
Neural Network	7.6	8.9
% error	8	5

Table 4-6 Average Air Velocity Results - Multiple Trains

Tunnel 1 (before the shaft)		
	Condition 1 (2 Trains)	Condition 2 (3Trains)
SES	5.6	6.1
Neural Network	5.0	5.6
% error	10	9
Tunnel 2 (after the shaft)		
	Condition 1 (2 Trains)	Condition 2 (3Trains)
SES	7.1	7.9
Neural Network	7.2	8.1
% error	2	3

Table 4-5 and 4-6 show that, results obtained by the proposed approach for simulating effect of multiple trains are in agreement with SES results.

4.3 Prediction of Unsteady Velocity Profile in a Complex Metro Station

In this study, “Hastane” Station of Ankara Metro System is simulated using the proposed method. “Hastane” Station has a typical architecture and is surrounded with two tunnels which connect the station to its neighbouring stations, “Demetevler” and “Macunköy”. In “Macunköy” side, connection tunnel is about 1045 meters and meets the ground before the vehicle reaches to “Macunköy” Station. On the other hand, in “Demetevler” side, tunnel is about 825 meters and connects directly to “Demetevler” Station without opening to atmosphere. All stations are equipped with ventilation shafts, used for both piston effect reduction and emergency ventilation purposes. Satellite view of the system is presented in Figure 4-4, 4-5 and 4-6.

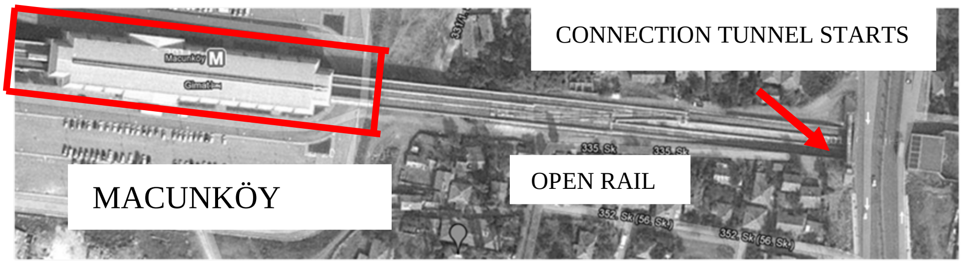


Figure 4-4 “Macunköy” Station and Connection Tunnel Entrance [63]

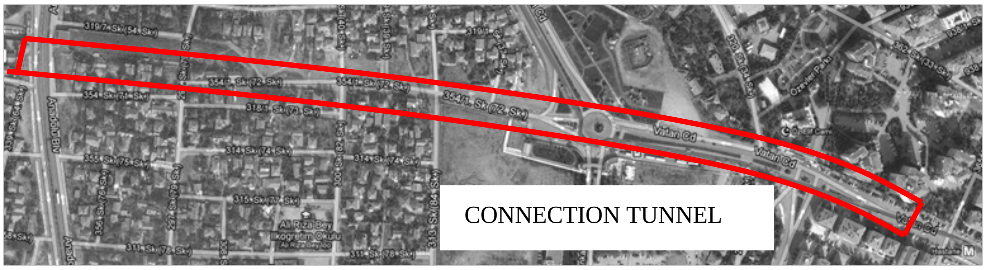


Figure 4-5 Connection Tunnel between “Macunköy” and “Hastane” Station [63]

Figure 4-6 “Hastane” Station and Surrounding Tunnels [63]

“Hastane” Station is a 2 floor station consisting of a platform and a concourse level. Platform level is connected to Concourse level through 2 staircases. Concourse level has also 2 staircases which connect the whole station structure to ground level. A schematic representation of the station is presented in Figure 4-7 and geometric details of the system are given in Table 4-7.

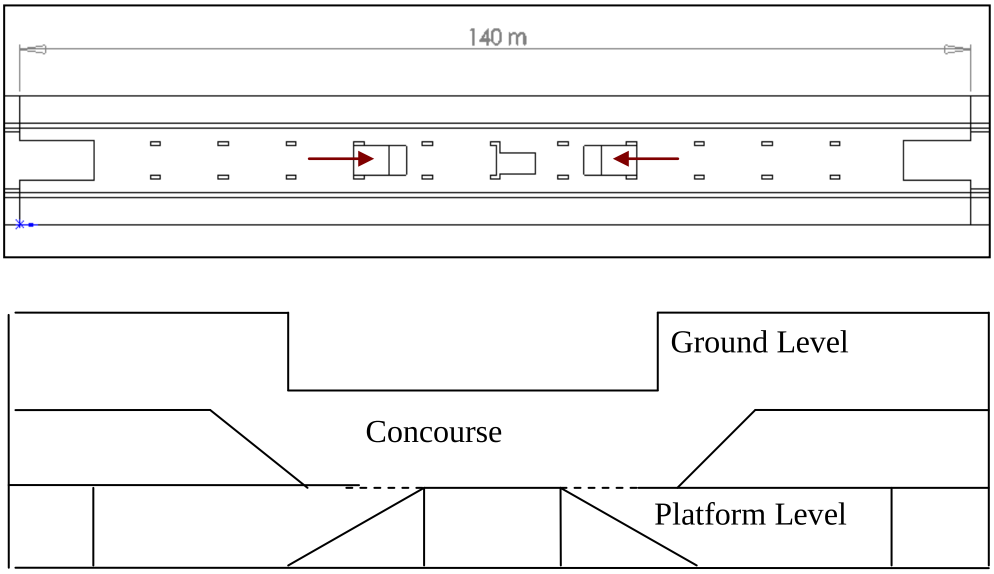


Figure 4-7 Schematics for Top and Section Views of “Hastane” Station

Table 4-7 Geometric details of "Hastane" Station and its surrounding tunnels

	Section	Segment	Length (m)	Area (m2)	Tunnel Type
Macunköy Side Tunnel	1	11	1039	18.9	Bored
	1	12	5.5	25.2	Cut-Cover
	Vent shaft	110			
HASTANE STATION	20	201	5.5	25.2	Cut-Cover
	20	202	11	27.4	Station
	3	31	39	71	Station
	4	41	10	29.4	Station
	6	61	10	71	Station
	7	71	6.5	27.4	Station
	9	91	3.5	71	Station
	10	101	10	29.4	Station
	12	121	40	71	Station
	13	131	10	27.4	Station
	13	132	5.5	25.2	Cut-Cover
	Vent shaft	220			
Demetevler Side Tunnel	21	211	5.5	25.2	Cut-Cover
	21	212	400	18.9	Bored
	21	213	417	18.9	Bored

Field measurements for air velocities induced by trains in "Hastane" Station in Ankara [27] are used in this case study. Velocity values are obtained in the cross section given in Figure 4-8.

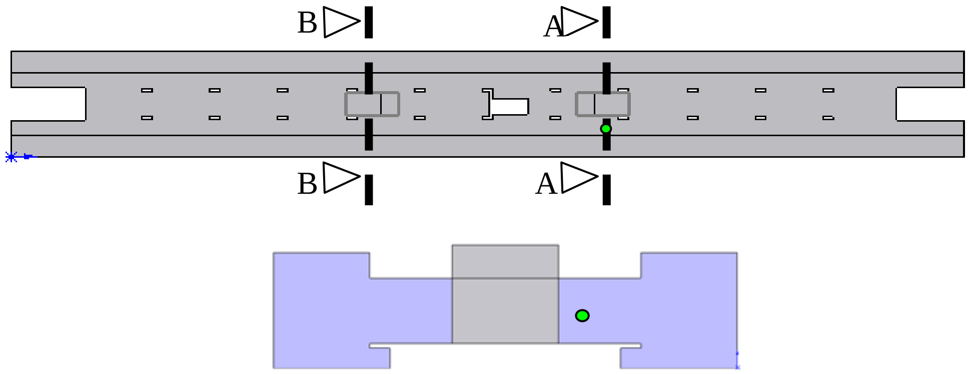


Figure 4-8 Schematics for Measurement Position (Section A-A) and Additional Run Location (Section B-B)

In Figure 4-9, time dependent velocity profile measured in Section A-A is presented together with the results obtained by SES simulations for the same location.

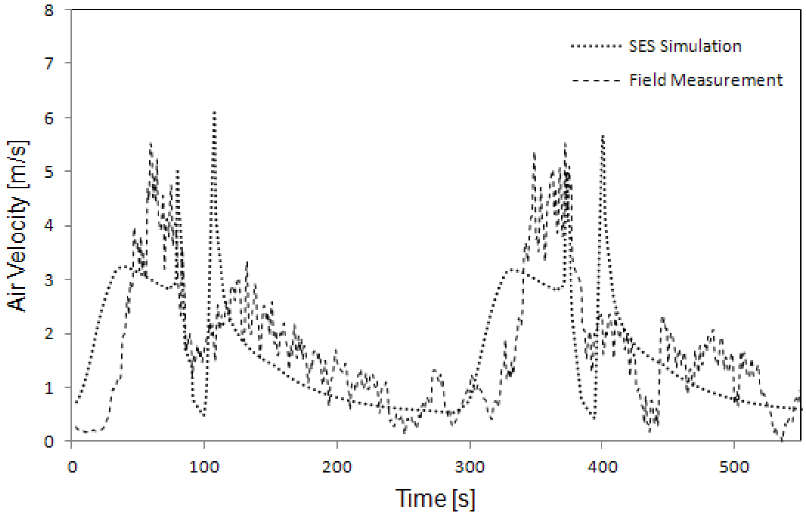


Figure 4-9 Time dependent Velocity Profile for Section A-A

A Simulink model, presented in Figure 4-10, is constructed using the developed prediction tool. In Table 4-8, data for the train used in SES and neural network simulations is presented. One should note that, introducing same system to SES software costs an input text file of about 2500 words. Although simulation times are comparable, proposed method is much superior then SES when system modelling is considered.

Table 4-8 Data for the Train

Train Length [m]	180
Train Frontal Area [m^2	13.6
Maximum Velocity of the Train [m/s]	20
Frontal Drag Coefficient of the Train	0.475
Skin Friction Coefficient of the Train	0.023
Maximum Train Entrance Velocity to Station [m/s]	11
Maximum Train Exit Velocity from Station [m/s]	15

In the simulations, 2 consecutive trains with headway of 300 seconds are considered and induced air velocity by these 2 trains is obtained.

In the model, wall friction factor is taken as constant since flow is expected to be turbulent in most of the cases. For rough concrete, an approximate value of 0.02 is assumed. In addition to friction factor, all minor head loss coefficients associated with the geometry of the system, together with drag and skin friction coefficients are also taken as independent of velocity since expected air velocities are within a narrow range of the same order.

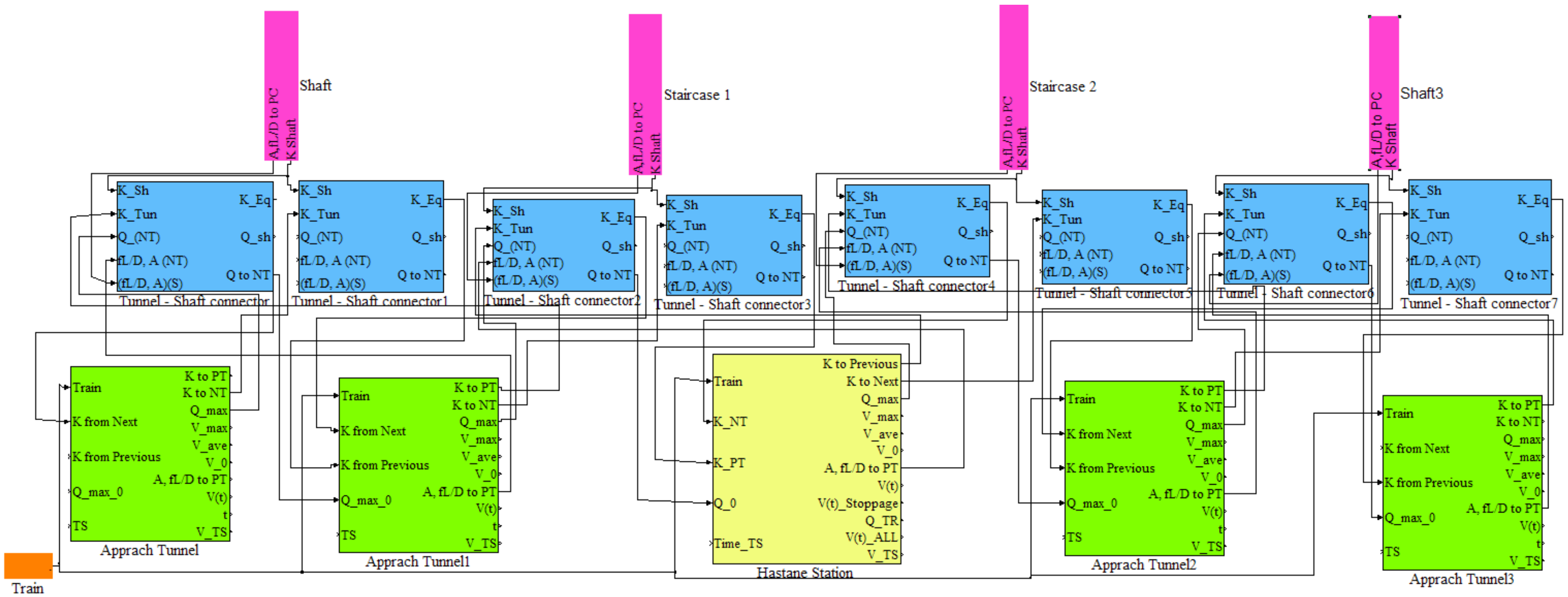


Figure 4-10 Simulink Model for Case Study 3

Staircases and ventilation shafts are modelled as if they were both ventilation shafts since they both correspond to openings to atmosphere through some minor head loss coefficients due to change in areas of flow passages inside these structures.

For staircases, approximated as ventilation shafts, flow passages are composed of the concourse level corridors, doors, glass panels and staircases that connect the concourse level to ground level. Although concourse level could also be modelled within the system, it is approximated as a lumped loss and included in the minor head loss coefficient of the staircase model. Same approach is also adopted in SES model of the system in the reference study.

There is another approximation in the model which assumes the stoppage of the train as *sudden.* Although the actual vehicle stops at the station platform with a constant deceleration, approximate model assumes the sudden stoppage of the vehicle. Consequences of this assumption are discussed in the results and conclusions part in detail with the aid of graphical results presented in comparison with SES results and field measurements.

Proposed method is used for approximating the periodic velocity profile induced by consecutive trains arriving at and leaving the station with a predetermined headway of about 300 seconds. Before presenting the results predicted by the approximate method, in Figure 4-11, important instants of vehicle movements are presented.

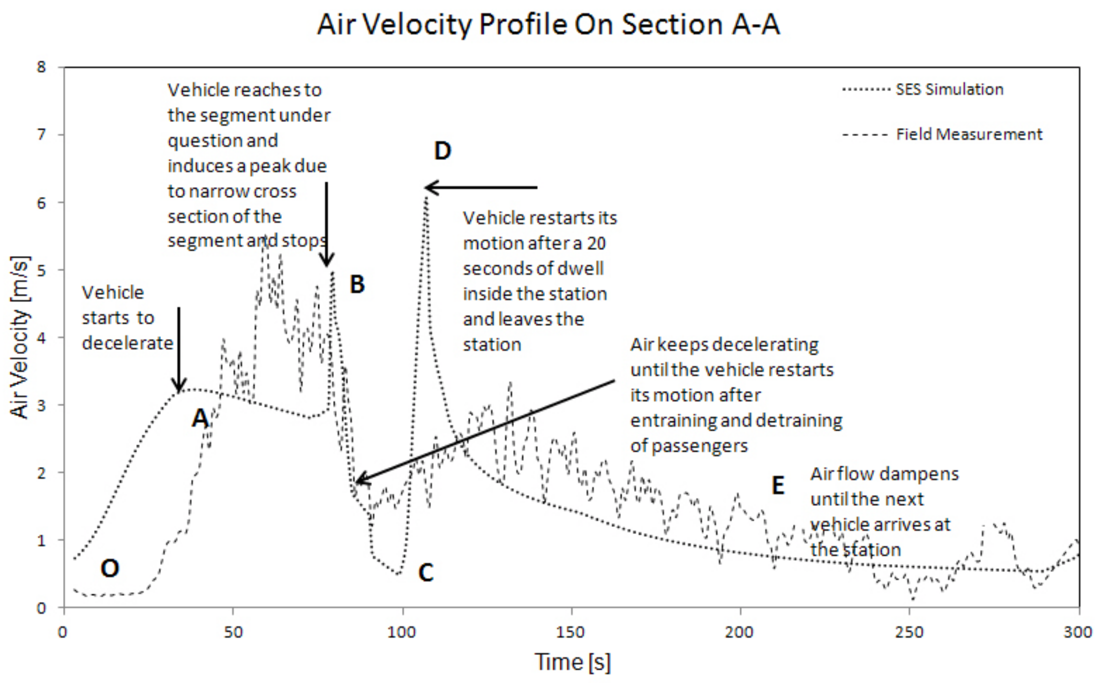


Figure 4-11 Critical instants of train movements on induced air velocity profile

Proposed method is used for predicting all peaks presented in Figure 4-11 together with the time dependent velocity profile within the intervals of train stoppage inside the station and departure of train from the station.

In Figure 4-12, results predicted by neural network model are presented in comparison with the SES results and field measurements.

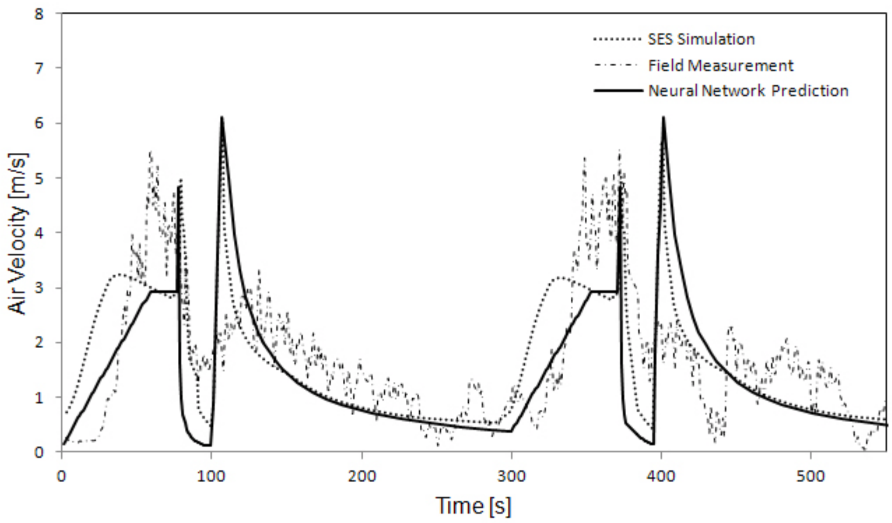


Figure 4-12 Air Velocity Profile at A-A Section Predicted by the Model

In Figure 4-12, it is shown that, important instants at which the vehicle arrives at the station, stops, restarts its motion and leaves the station are predicted in agreement with SES results. One should note that Figure 4-12 is a segment of a longer time period consisting of peaks induced by multiple trains. This is the reason for field measurement and SES results not starting from zero velocity at the origin. In Table 4-9, values of time dependent air velocity predicted by neural networks are presented together with SES results. One can see that, for time instants at which the effect of train acceleration and deceleration are dominant, developed tool cannot predict results with acceptable accuracy. In addition, difference between the dampening of air velocities in case of sudden stoppage of the vehicle and the vehicles leaving the station are also observed. One can see that, air velocity is predicted with the time dependent neural network to fall to lower values after the vehicle stops in the station when compared to SES results. This is because the model assumes sudden stoppage of the vehicle while the SES model includes the effect of deceleration of the vehicle.

Table 4-9 Air Velocity Results for Section A-A

Time	SES	NN	% error
0	0.74	0.15	80
20	2.3	1	57
40	3.2	1.9	41
60	2.98	3	-1
80	4.95	5	-1
100	0.49	0.12	76
140	1.6	1.8	-13
160	1.3	1.2	8
180	0.98	0.9	8
200	0.82	0.8	2
220	0.7	0.6	14
260	0.59	0.5	15
280	0.5	0.4	20
300	0.81	0.4	51

Note that, in Table 4-9, time instants of 0, 20, 40, 60, 100, 280 and 300 are the points at which the train acceleration and deceleration is most dominant. Developed tool can be further improved to predict these instants by inclusion of train acceleration and deceleration characteristics. One should also note that, developed tool predicts 38/h air exchange for the station while SES predicts 35/h which corresponds to a percent error of about 8%. Predicted air exchange rate is within the acceptable error range.

When both SES and proposed method are considered in comparison with the field measurements, they both lack in estimating the fluctuations in air velocity but one should note that, SES and proposed method are used for obtaining average time dependent velocity in the cross section and do not include 3D effects. In addition, measurement data is taken from a single point which does not possibly represent the actual average flow rate and velocity. Another major difference is the duration of peaks in vehicle entrance, which is longer in actual field data while SES and proposed method's results show an instantaneous rise in the air velocity. This is probably because of the other means like wind and operation of ventilation equipment during field measurements. Results can still be considered as sufficient when important parameters like maximum air velocity and total amount of air brought to station by piston effect are considered.

For further discussion on the proposed method in comparison with SES results, an additional location in the station is investigated. Although there is not measurement data at that location, results of SES software and proposed method are compared for the Section B-B presented in Figure 4-8.

In the location depicted as Section B-B in Figure 4-8, it is expected that the flow velocity should be greater than the previous location. A part of the flow escapes from the first staircase which is on the left hand side of the station resulting in less flow rate at the cross section at which the second staircase is located. In Figure 4-13, results of proposed method are presented together with SES results for the same location.

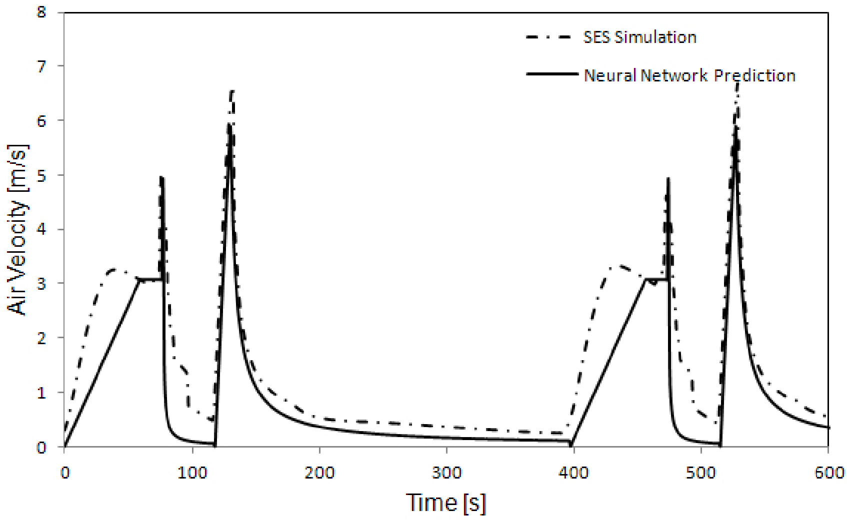


Figure 4-13 Air Velocity Profile at B-B Section Predicted by PISTON Model

Time dependent velocity profile of air at section B-B is presented in Figure 4-13. It is seen that, effect of flow split in 1st stair on flow velocity at section B-B is apparent although a small amount of flow escapes from the 1st stair. Success of proposed method should be attributed to the success of trained neural networks. Training data set is carefully prepared considering the commonly encountered values of system parameters and this led to successful prediction of air velocity in an actual metro station.

In Figure 4-13, one can also see the effect of sudden stoppage assumption made for the vehicle. While the air velocity decreases down to 0.5 m/s in SES results, neural network trained with time dependency predicts this minimum value as approximately zero. This difference in minimum velocity has influence on the value of next peak since it corresponds to less initial momentum for the next peak. Table 4-10 presents the values for time dependent air velocity predicted at Section B-B.

Table 4-10 Air Velocity Results for Section B-B

Time	SES	NN	% error
0	0.24	0.05	79
20	2.2	1	55
40	3.3	2	39
60	3.1	3	3
80	5	5	0
120	0.5	0	100
130	6.4	5.9	8
140	2.3	2	13
160	1.1	1	9
180	0.7	0.5	29
200	0.55	0.36	35
220	0.49	0.28	43
260	0.44	0.2	55
280	0.41	0.18	56
300	0.37	0.15	59

Note that, in Table 4-10, at time instants of 0 to 60th seconds and after 120th second, velocity values cannot be predicted with expected accuracy. These instants also correspond to the time intervals at which the train acceleration and deceleration is dominant. Longer travel times result in longer steady motion of air and can be predicted by the proposed tool better. In addition, air exchange rate predicted for the segment is predicted to be 16/h while SES calculates the same parameter as 19/h. About 15% error in air exchange rate is still beyond the acceptable range but can be further improved with inclusion of train acceleration feature to the model.

First region of the velocity profile deviates from the SES results strongly because of the changing velocity of the vehicle. On the other hand, although the profile is not as successful, predicted maximum value is in agreement with SES results.

Time dependent air velocity profile in “Hastane” Station of Ankara City Metro System is obtained using the simulation tool developed with neural networks and analytical methods. Results of proposed method are compared with SES simulation results and field measurements for the same station. Following conclusions are drawn.

- Proposed method is capable of predicting the important instants like the peaks of the velocity profile. These peaks are important since the peak velocity magnitude in the platform level is restricted by a value in most of the metro systems around the world.

- Although there are limits on maximum allowed air velocities on platform level, for most of the time it is not practically possible to keep maximum air velocity under the limiting values. In such cases, the duration of the peak is supposed to be less than about 10 seconds which is considered to be acceptable in local operations. Proposed method is capable of predicting the duration of the peaks so can be used for practical design purposes.

- Another important parameter in underground station design is air exchange rate of the platform level. As long as fresh air can be supplied into the station by piston effect of the vehicles, less additional air handling unit is required which is an economic optimization of the system. In calculation of the air exchange of platform, only the fresh air being sucked from the staircases and ventilation shafts are considered while the air brought by the train from inside the tunnel does not contribute to the exchange rate. In this manner, time interval between A-B in Figure 4-11 is not taken into account since it corresponds to the air brought from inside the tunnel. On the other hand, the interval between C and D corresponds to the time interval within which the vehicle restarts its operation after its dwell and sucks air from shaft, staircases and tunnels. So this interval is important in obtaining air exchange rate of the station and is obtained with the proposed method in good agreement with SES results.

- Velocity profile predicted by proposed method can further be improved by inclusion of acceleration and deceleration of train to the model. By a varying vehicle velocity, time interval between A and B, and B and C would be predicted much better.

- Simulink model of proposed method is superior to SES when pre-processing time is considered. User can built the whole model within minutes while SES requires quite a long pre-processing and data input time about 4 to 5 hours for an experienced user.

- Proposed method can be used for preliminary design purposes. Required modifications of the system parameters can be predicted prior to execution design of the metro system optimizing the system and reducing the time of rework.

CHAPTER 5

CONCLUSION

A data driven method for approximating time dependent vehicle induced velocity profile is proposed and verification studies for the proposed method is conducted. Artificial Neural Networks are used as the data driven method, together with analytical methods for obtaining the critical instants and intervals of time dependent air velocity profile in underground systems.

Proposed method basically utilizes feed-forward back propagation neural networks for predicting maximum and average air velocities and the time dependent velocity profile of air in the intervals where train leaves the tunnel or stops and dwells in underground metro systems. In the model metro trains are assumed to be the only means that induce air flow inside the tunnels and stations, implying piston effect only. In addition to neural networks, analytical methods for obtaining time dependent profile of air velocity are also used.

In neural network training, non-dimensional parameters, which are generated with system variables like area, length, friction coefficient, etc., are used. Use of non-dimensional groups obtained with the system parameters, instead of dimensional parameters resulted in a simplified neural network structure. This also results in a reduced number of input parameters and a more efficient training. Considering train length, area, drag coefficient and speed, together with tunnel length, area and friction coefficient, it would cost 4^7 (16,384) runs to use 4 different values for each parameter. On the other hand, the use of 4 non-dimensional groups would only require a total of 4^4 (256) runs. Reduction in the number of runs has a dramatic effect in reducing the computation time for network training.

Proposed method is verified through 3 case studies which consider 3 different systems as cases. The first case study is done for questioning the proposed method in its generalization capability for systems about which the trained neural networks are not aware of. Neural network are used for predicting maximum induced air velocity in a multi-shaft, multi-tunnel system although they are trained for just a single tunnel. Results of the first case study show that, trained neural network for maximum velocity, produces results in agreement with the authoritative software, SES. 10% error is adopted as the success criteria for the neural networks, since this value is within the range of the accuracy of the SES Software itself. Note that, success of neural network in predicting maximum air velocities induced by the trains can be considered as a major contribution to application of neural networks in moving boundary problems. A detailed discussion about the issue is presented in discussion section of this chapter.

Proposed method, which has proven to be successful in predicting maximum air velocity for multiple tunnels, is further tested for being applicable in multi-vehicle systems which are the actual case in most of the metro systems. The second case study basically focuses on the effect of multiple trains simultaneously on operation in the same tunnel-shaft system. 2 train groups, one with 3 consecutive trains and the other with 2, are simulated with the proposed method. Instead of applying a major modification to the neural network, a slightly modified input data, in which the train length to diameter ratio and the frontal drag coefficient are factored with the number of the trains, is used. As a result, neural networks with the modified input data produce maximum and average velocities in agreement with SES software. Note that, simulating the effect of multiple trains on induced air velocities became a straight forward procedure just because the neural networks are trained with non-dimensional parameters instead of dimensional ones.

As a third and the last case study, proposed method, utilizing all analytical methods and 3 neural networks responsible for approximating maximum and average induced air velocities and the time dependent velocity of air in case of train stoppage or departure, are used for simulation of an actual metro system. In the third case, “Hastane” Station of Ankara City Metro System is simulated. This case is a complete verification study since it involves the utilization of all proposed methods within the scope of this study. Results obtained by the proposed method are compared with the field measurement data which contributes to the study considerably. In addition, same case is also modelled with SES software and all results are considered in comparison with each other. Results of the 3rd case study, which can also be considered the ultimate outcome of the thesis, can be summarized as follows;

- Proposed method is capable of predicting the important instants like the peaks of the velocity profile. Note that, for a preliminary study in metro system design stage, amplitudes of the peaks are sufficient for taking precautions about geometric configuration of ventilation shafts.

- In addition to the amplitudes of the peaks, duration of the velocity peaks is also approximated with good accuracy when compared with SES. Duration of peaks is of great importance in cases where the limiting maximum air velocities cannot be achieved with practical modifications of the system design.

- Amplitudes of the peaks, together with their corresponding durations contribute to the design of a metro system by defining the part of the flow rate occurring within the tunnels and the station. Air exchange of a station is the second major design parameter which has great influence on the station comfort and operation cost of the system. As long as fresh air can be supplied into the station by piston effect of the vehicles, less additional air handling unit is required which is an economic optimization of the system. In calculation of the air exchange of platform, only the fresh air being sucked from the staircases and ventilation shafts are considered while the air brought by the train from inside the tunnel does not contribute to the exchange rate. In proposed method, artificial neural networks predict the maximum air velocity which is used as the initial condition of air dampening period. Third neural network, considering time as one of its inputs, can be used for calculating the amount of fresh air brought by the result of piston effect. Results obtained by the proposed method show that, predicted dampening periods are also in agreement with SES results.

- Velocity profile predicted by proposed method can further be improved by inclusion of acceleration and deceleration of train to the model. Sudden stoppage assumption for the vehicle result in a faster dampening of air velocity which also effects the maximum value of the next peak induced by the train during its departure from the station. By inclusion of the acceleration and deceleration capability of the trains into the model, air velocity dampening periods can be predicted with much more accuracy.

- SES software requires a tedious pre-processing. Developed Simulink model of proposed method is superior to SES when pre-processing time is considered. User can built the whole model within minutes while SES it takes about 4 to 5 hours for an experienced user to model the system in SES.

- With the practical use of it, proposed method can be used for preliminary design purposes. Sensitivity studies on system parameters can be done quickly and precautions about the comfort criteria of an underground system project can be taken by the aid of the developed Simulink model.

- Although there is not any systematic approach for selection of neural network type and network architecture configuration, some heuristics are usually helpful in neural network studies. In this study, in addition to Cybenko's well known theorem, an approximate analytical solution for vehicle induced air velocity is obtained. Obtained relation is questioned in its characteristics to see whether the neural network to be used should or should not have a memory in its structure. Obtained approximate relation shows that, induced air velocity can be expressed explicitly with the input parameters so no memory is required, thus there is no need to use a recurrent neural network.

- Number of neurons in hidden layer has effect on the performance of the neural network. Higher number of hidden neurons does not necessarily mean a better neural network performance so a trial and error procedure is most of the time is mandatory. On the other hand, in order to start with a reasonable assumption on the hidden layer neurons, some heuristics can be used. In this study, a heuristic, stated by Weigend et al., which defines an interval within which the number of hidden layers should fall, is used. Having obtained the interval, different number of hidden layers that fall within this interval is considered and the statistically best performing number is selected.

- Coefficient of determination, Mean Square Error and percent Error are used as the performance parameters to evaluate the goodness of model approximation. These are commonly used performance measures in prediction of continuous variables. Training and test runs show that, MSE value does not exceed 10^{-3} while the least value of R^2 is 0.987 which both implies a high level of goodness of the approximation.

Artificial neural networks are commonly used in solving engineering problems almost to any level of complexity as long as there is enough data about the physical problem in hand. Most of the time, these data are obtained through field measurements where the exact relationship between the variables are not known. In addition, many of the relations that are currently based on empirical studies are also good candidates to be considered by the aid of neural networks.

Most of the literature referenced to during this study show that, application of neural networks from selection to training and execution, is not still a systematic approach and includes quite an amount of trial error and heuristics. This is an expected result when the nature of the neural networks and their application areas considered. In this study, in addition to the preliminary trial and error effort, an approximate analytical solution for induced air velocity is proposed and obtained relation of the parameters formed the basis for the neural network selection.

In this study, instead of using field measurement data for neural network training, a reliable and authoritative tool, SES Software, is used for data generation and testing. Having such a tool available, neural network training and tests are much simpler when compared to the studies those are very limited in data to be used. This turns out to be an advantage in a neural network based study.

Technical Contribution of the Dissertation

The ultimate purpose of the study was to solve the time dependent velocity profile in metro tunnels and station with neural network approach which inherently possesses 3 major contribution to the literature;

- *Despite of the overwhelming effort on solution of engineering problems with neural networks, no significant effort is present for solving one dimensional air flow inside metro tunnels.*
- *A novel method is proposed for solving the dependent variable of velocity, without solving the pressure, which are strongly coupled through momentum equation.*

- *Neural networks, most of the time trained for a definite solution domain, are not forced or elaborated for being used for a different solution domain. This study forces the neural network for operating in an environment with which it is not familiar.*
- *A simulation tool is developed which can be considered as a substitute for SES Software. In addition, developed tool can be further improved in contrary to SES with its data driven nature. Field data for pressure, temperature and velocity can be used for training new neural networks and a sophisticated simulation tool can be obtained.*

First contribution mentioned above is apparent when literature is traced with the relevant theories of one dimensional flow and neural networks. The difficulty of conducting experimental studies in operating metro systems results in a very limited amount of field data which is the major constituent of a neural network approach. In addition, in case these limited data is used for training purposes, it is almost impossible to conduct test runs for the trained neural networks. These difficulties, most probably, are the reasons for not having enough effort in this discipline.

Second contribution, to the field of fluid mechanics, can be considered as another major output of the study. Note that, most of the numerical and graphical solution schemes, including MOC, consider both pressure and velocity. In this study on the other hand, velocity is solved without needing to solve the pressure field inside the domain. Having already obtained the velocity field, it is now much easier to continue with the time dependent pressure, which can be considered as a future work.

When considered from a neural network point of view, the third contribution stated above can be considered as one of the key outputs of the study. Neural networks are commonly used for fixed domain of definition and solution. For most of the time, the environment for which the neural networks are trained for does not change while only the values of parameters that define the environment change. In such a case, neural network trained for the solution is expected to approximate the results for input data it has not seen before. On the other hand, in the very case of this study, a neural network is trained for a single tunnel domain with selected parameters that are believed to be sufficient to define the single tunnel environment. By the proposed analytical solutions and methods, the neural network trained for a single tunnel is equipped with the capability of generating solution for a completely different domain including practically any additional component like staircases, stations, ventilation shafts and multiple tunnels.

Proposed method is a data driven model so it can further be improved by field measurement data. A laboratory set-up such as shallow water approximation of incompressible flow of air can be used for collecting data and neural networks can be trained with real data instead of data produced by SES. By experimental results, proposed method can be improved further to get more superior than SES by introduction of more data about physical phenomena. In addition, pressure measurements can be done on an actual system or laboratory setup and results can be used for improving the model with the capability of pressure approximation.

Another further study, considering road vehicle tunnels, can be also considered as a valuable extension of this study. In road vehicles, there is always a huge amount of piston effect together with high rate of exhaust emissions of vehicles which are determined by empirical data. Tabular characteristics of emission calculations and piston effect make road vehicle simulations an appropriate candidate for proposed method in this thesis.

Standalone software with a practical user interface can be developed using the model proposed in this study. Inclusion of neural networks that are trained with experimental data and field measurements can further develop the capabilities of the proposed approach. Pressure prediction and inclusion of energy equation for solution of piston effect in high gradient highway tunnels can also be considered as future extension of this thesis which has broad application areas for the last decade especially in Turkey.

Compressible flow of air in high speed train tunnels is another field of research that can be supported with the experience gained during this study. Assuming compressible flow for air in metro tunnels and stations is also a improvement to the current effort since this assumption would yield much accurate results in case the heat transfer through vehicle auxiliaries like resistor grids and climate systems dominate the ambient conditions.

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APPENDIX-A

COMMON ACTIVATION FUNCTIONS FOR NEURAL NETWORKS

Depending on the nature of the problem and data set in hand, various types of activation functions can be used in neural networks. Activation functions are also known as squashing functions and produce the layer output. Following are the details of the activation functions;

Threshold Function: This type of activation functions are commonly used for classification problems. It basically returns an output of 1 if the induced local field, i.e. the weighted sum of input data is nonnegative or 0 if otherwise. In engineering, threshold function is referred to as Heaviside Function. In equation (A.1), definition of the threshold function is given.

$$f(v) = \begin{Bmatrix} 1 & if & v \geq 0 \\ 0 & if & v < 0 \end{Bmatrix} \tag{A.1}$$

Where induced local field, v is expressed as $v_k = \sum_{j=1}^{k} w_{kj} x_j + b_k$. Note that, induced local field of the neuron also includes a bias term b_k for the most general case. Graph of the Threshold function is presented in Figure A.1.

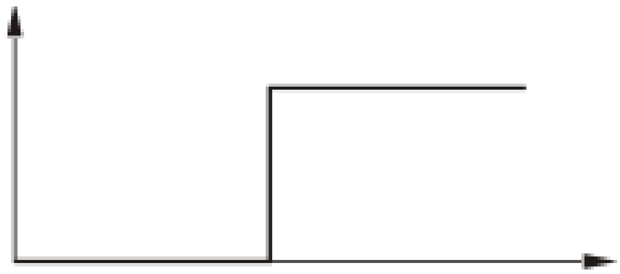

Figure A.1 Threshold Function

Piecewise-Linear Function

This type of activation function is also referred to as saturating linear function, output of which can take the value of -1 or 1 beyond its saturation limits, and a proportional value at the linear region. In equation (A.2), mathematical definition of the piecewise linear activation functions is presented.

$$f(v) = \begin{cases} 1, & v \geq +\frac{1}{2} \\ v, & +\frac{1}{2} > v > -\frac{1}{2} \\ 0, & v \leq -\frac{1}{2} \end{cases}. \tag{A.2}$$

In Figure (A.2), a piecewise linear function with bipolar saturation regions is presented.

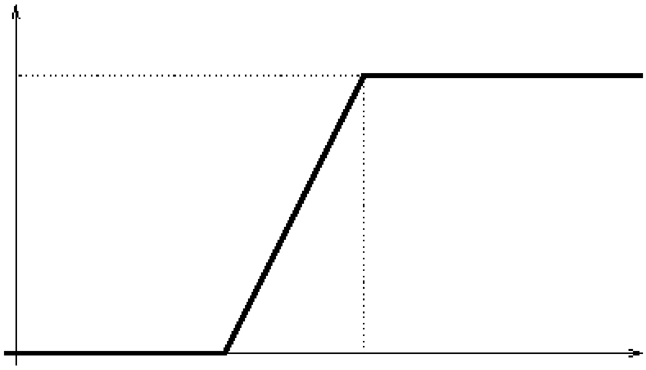

Figure A.2 Piecewise Linear Function

Sigmoid Function

This type of activation function is basically an s-shaped continuous differentiable function, which is most commonly used for construction of neural networks. Sigmoid type of activation functions are especially used for approximating continuous functions and are used also in the method proposed in this thesis. An example of a sigmoid function is hyperbolic tangent function which is $f(v) = \tanh(v)$. Plot of the hyperbolic tangent function is given in Figure A.3.

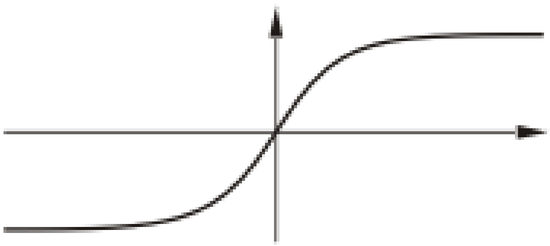

Figure A.3 Tangent Hyperbolic Function

APPENDIX-B

WEIGHTS OF THE NEURAL NETWORKS

Details of the neural networks trained for maximum, average and time dependent air velocities are given in Table B-1, B-2 and B-3. Weight and Bias values are given for the following form of expression for network output;

$$y = w_2 \Psi\left(w_1 x + B_1\right) + B_2 \tag{B.1}$$

Where

$$w_1 \in \Re^{16\times 4}$$
$$w_2 \in \Re^{1\times 16}$$
$$B_1 \in \Re^{16\times 1}$$
$$B_2 \in \Re$$

X is the non dimensional input vector for neural network and given by:

$$x = \left[f_{tunnel} \frac{L_{tunnel}}{D_h}, \frac{A_{train}}{A_{tunnel}}, \frac{L_{train}}{D_{train}}, C_{D\_overall} \right] \tag{B.2}$$

Ψ is the activation function of the neural network.

Table B-1 Weights for Maximum Velocity Neural Network

W_1				W_2	B_1	B_2
0.14162	-0.18763	0.02181	-0.07926	-0.39140	0.035128	-0.19025
-0.17155	0.17834	0.01612	0.00106	0.38603	0.037123	
-0.03126	0.10428	0.01743	0.08480	0.15404	-0.02661	
-0.05311	-0.21922	-0.19329	1.31460	0.59503	-1.0675	
-0.13471	-0.44658	-0.62567	0.10938	1.38510	0.1843	
0.00871	0.03219	0.20801	-0.34388	0.56297	0.32139	
2.34920	0.02248	-0.24805	-0.46006	-1.58170	3.2824	
0.12306	-0.31731	0.00881	-0.23019	-0.53898	0.34692	
0.07064	0.82605	-1.55990	-1.20910	-1.70250	-2.0757	
-0.06381	0.17898	0.00143	0.12481	0.28032	-0.10684	
0.16722	-0.16271	-0.04630	0.04671	-0.29985	-0.07762	
-0.04432	0.13459	0.01504	0.11126	0.21520	-0.06969	
-0.00611	0.02264	0.00631	0.02368	0.03357	-0.00105	
-0.09815	0.27626	-0.00824	0.18920	0.44404	-0.26264	
0.16932	0.44636	0.33281	0.31589	0.88990	-0.64311	
-0.12894	-0.02064	-0.40731	0.45773	-0.94168	-0.60482	

Table B-2 Weights for Average Velocity Neural Network

W_1				W_2	B_1	B_2
-1,69350	0,10122	-0,17481	0,01085	-1.35680	-1.14390	1.2443
0,42787	1,0417	-0,84182	-0,60184	1.05420	1.01770	
-0,81062	-0,35500	0,74827	0,76015	-0.64710	0.14145	
0,86823	-0,57529	0,65278	-0,19720	-1.29450	0.96629	
-0,08211	0,51328	-0,09275	-0,62488	-0.92347	0.58577	
-1,40160	0,10782	0,31887	0,69368	0.82679	-0.13661	
0,21901	-0,55167	-0,50790	-0,20075	0.80429	-0.21847	
-0,19885	0,46191	-0,99940	0,21555	-1.31598	-0.58329	
0,39391	0,06040	0,06851	-0,08645	-0.71545	0.64689	
-1,18350	-0,35343	-0,18113	-0,14101	-1.44490	1.32650	
-0,21725	-0,15465	0,15169	0,13707	-0.36106	0.11785	
0,28402	0,10913	0,03146	-0,01458	-0.63177	0.41497	
0,73828	0,77322	-0,72149	0,04143	-1.16890	0.89293	
7,84260	0,06401	-0,13662	0,01794	3.03920	9.16290	
0,18677	0,83063	0,12257	0,26427	0.89465	0.55744	
-0,34880	-0,18521	0,03000	0,04891	0.72795	-0.59038	

Table B-3 Weights for Time Dependent Air Velocity Neural Network

W_1	
-3.488	-7.471
-0.340	0.974
1.407	1.347
1.595	3.229
-3.329	0.795
0.307	2.796
-0.110	3.258
-0.892	-1.042

W_2							
-6.759	2.512	0.480	0.281	-2.671	0.626	-0.025	-2.171
0.858	0.912	-0.959	-0.829	-3.422	0.131	0.119	-2.176
0.550	2.532	-0.290	-0.890	0.600	2.424	-4.289	1.183
-0.851	2.084	1.870	0.317	-2.641	4.169	4.302	-4.018
-0.202	-0.247	1.006	-0.166	0.145	-2.112	0.304	-0.704
0.398	0.096	0.440	0.577	-0.895	0.809	1.064	-1.047
0.634	0.999	-0.188	-0.937	0.108	-3.145	-0.638	-1.448
0.529	-0.317	0.278	-0.403	0.188	-0.681	-0.622	0.035
-0.076	-0.160	-0.415	0.002	-0.270	-1.141	0.945	-0.858

W_3
3.96040
2.31850
-0.48225
9.89350
-3.45520
2.35230
1.09990
-3.54390
1.81200
-6.91860

B_1
3.967
-0.613
0.130
-1.671
-3.241
3.085
32.611
-1.433

B_2
-1.496
-1.483
1.134
-0.232
0.833
-0.316
0.837
0.812
-0.613
2.204

B_3
5.2132

CURRICULUM VITAE

PERSONAL INFORMATION

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EDUCATION

Degree	**Institution**	**Year of Graduation**
M.S.	MIDDLE EAST TECHNICAL UNIVERSITY Department of Mechanical Engineering	**2007**
B.S.	MIDDLE EAST TECHNICAL UNIVERSITY Department of Mechanical Engineering	**2004**
High School	Antalya Anatolian High School	**1999**

WORK EXPERIENCE

Year	**Place**	**Enrollment**
2011 –	Taru Engineering Inc.	Board Member
2006 – 2011	Taru Engineering Inc.	R&D Engineer
2004 – 2006	Ostim Investment Co.	R&D Engineer

FOREIGN LANGUAGE

English

PUBLICATIONS &PROCEEDINGS

- Koç. G.K.. Albayrak. K.. Sert. C.. “Utilization of Neural networks for Simulating Vehicle Induced Air Velocity in Underground Tunnels”. European Congress on Computational Methods in Applied Science and Engineering, Vienna, Austria, 9-15 September 2012.

- Koç. G.. Eralp. O.C.. “Sıvı Boru Hattı Sistemlerinde Zamana Bağlı Akış Simülasyonu için Kolay Kullanımlı Bir Yazılım”. 6. Pompa Vana Kongresi. 2008
- Eralp. O. C.. Kayılı. S.. Kayhan. C.. Koç. G.. “Application of Jet Fans for Emergency Ventilation in Tunnels of Underground Transportation Systems”. VII. International HVAC+R Technology Symposium and Exhibition. 8-10 May 2006 (in Turkish)

PROJECTS PARTICIPATED

- Comfort and Emergency Ventilation Simulations and System Design for Üsküdar – Ümraniye – Çekmeköy Metro Line. İstanbul. 2012 (Continuing)

- Life and Fire Safety Design and Concultancy for Üsküdar – Ümraniye – Çekmeköy Metro Line. İstanbul. 2012 (Continuing)

- Consultancy for Fire and Life Safety of TCDD 1st Region Train Stations. İstanbul. 2011

- Emergency Ventilation Simulations and System Design for Maltepe PMA Structure in Kartal – Kadıköy Metro Line. İstanbul. 2012

- Piston Effect and Emergency Ventialation Simulations and System Design for Avrasya Road Tunnel. Yapı Merkezi. İstanbul. 2011

- Emergency and Comfort Ventilation (Piston Effect) Design and Simulations for Taksim Underground Pass to be Constructed by İstanbul Municipality. İstanbul. 2011

- Simulation of Tunnel Fires and Emergency Ventilation and Piston Effect; Design of the Emergency Ventilation System in Warsaw Line II Metro Line. Poland. 2010

- Tests for Evaluation of Piston Effects in Hastane Station Ankara Metro System METU. October 25th. 2008

- Simulation of Tunnel Fires and Emergency Ventilation and Piston Effect; Design of the Emergency Ventilation System in İstanbul Railway Mass Transit of Sanayi- Hacıosman Section. September 2008

- CFD Analysis of Station Fire in Sanayi Station. Atatürk Oto Sanayi Station. İTÜ Ayazağa Station in İstanbul Railway Mass Transit of Sanayi- Hacıosman Section. June -September 2008

- CFD Analysis of Station Fire in Başak Konutları-4. Çinçin Stations of İstanbul Başak Konutları-4 Kirazlı-1 Rail Transportation System. April 2007

- Simulation of Tunnel Fires and Emergency Ventilation and Piston Effect; Design of the Emergency Ventilation System in İstanbul Esenler Bağcılar Light Rail Transportation System. 2006

- Simulation of Tunnel Fires. Emergency Ventilation and Station Comfort. Design of the Emergency Ventilation System in Ulus – Keçiören Metro System.. Yüksel Proje AŞ.. 2005-2006

- Simulation of Tunnel Fires and Emergency Ventilation and Piston Effect; Design of the Emergency Ventilation System in Ankara Metro 3rd Phase. Güriş İnş. AŞ.. 2002-2003.

- Simulation of Tunnel Fires. Emergency Ventilation and Station Comfort. Design of the Emergency Ventilation System in Ankara Söğütözü-Çayyolu Metro System. Yüksel Proje AŞ.. 2003-2004

- Simulation of Tunnel Fires. Emergency Ventilation and Station Comfort. Design of the Emergency Ventilation System in Ankara Söğütözü-Karakusunlar Light-Rail Ankaray System. Yüksel Proje AŞ.. 2004

- Simulation of Tunnel Fires. Emergency Ventilation and Station Comfort. Design of the Emergency Ventilation System in Ankara Kızılay-Söğütözü Metro System–Preliminary Study. Güriş İnş. AŞ.. 2004

- Simulation of Tunnel Fires. Emergency Ventilation and Station Comfort. Design of the Emergency Ventilation System in Ankara Ulus-Keçiören Metro System –Preliminary Study. Yüksel Proje AŞ.. 2004

- Simulation of Tunnel Fires. Emergency Ventilation and Station Comfort. Design of the Emergency Ventilation System in Ankara Ulus-Keçiören Metro System. Yüksel Proje AŞ.. 2004

- Simulation of Tunnel Fires. Emergency Ventilation and Station Comfort. CFD Analysis of Station Fires. Design of the Emergency Ventilation System in Krakow Metro System – Poland. 2004

MEMBERSHIPS

Chamber of Turkish Mechanical Engineers (TMMOB)
American Society of Mechanical Engineers (ASME)

HOBBIES

Watching Barcelona. Playing Football. Watching and talking about Luis Nazario De Lima Ronaldo. “Il fenomeno”