A novel intelligent approach to enhance the performance of wind tunnel systems involving a delay

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Abstract— Recently, a large amount of researches have been focused on the developments and improvements of the security transportation through tunnels specially in the mountain regions. This paper is concerned with improving the security and performance of wind tunnel systems involving a delay in their dynamical process based on a novel intelligent technique to enhance their. A new alternative representation is first developed, which transfers the infinite dimensional nonlinear neural networks (NN) with time-delay in the states to a unique and exact alternative finite dimensional nonlinear generalized state space model with no delays in the states nor in the control input. This model is capable of generalizing results previously restricted to the non-delayed systems. This alternative model is divided into two subsystems, namely, a slow and a high subsystems as defined in [24]. The slow mode is then used in the stabilization process where the transient response is improved by using only one feedback control law, which can be easily implemented in a manner analogous in many respect to those obtained for conventional state space systems. The results obtained are much more direct and the presence of time delay in the dynamics of the wind tunnel system due to the Mach number does not result in any problem in designing its controller compared with those given by other methods, mainly because the present design procedure has allowed possible updating of the controller's parameters online with the change of the operating point without using any kind of numerical approximation. A grid computing through a computer network is also presented and used to control and enhance the performance of the tunnels based on an inelegant adaptive controller with minimal execution time as well as the minimal cost budget. A new optimal back propagation neural network (OBPNN) algorithm based on this grid computer network is developed. The usefulness and validity of the presented approach have been obtained and examined by numerical examples using GridSim Toolkit based on the derived adaptive intelligent model and the simulation process of wind tunnel systems involving a delay that are connected through a unified grid computing network is introduced.

Index Terms— Wind tunnels, Nonlinear neural networks (NN), A mach number, Adaptive Intelligence Model, . Time Delay Factor, Grid computing network, optimal back propagation neural network (OBPNN), GridSim Time Optimization.

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1 INTRODUCTION

RECENTLY rapid developments in controlling wind tunnels systems with time delays have generated a large amount of researches10]-[20],[28]-[42]. Often, drawing conclusions from these researches require the use of sophisticated closed form analyses that are creating wind within virtual environments (e.g., wind display) and challenging problem with a potential to develop immersive atmospheric display for virtual reality systems[32].In virtual environments, the synergistic mechatronics design, sensing, and control of a scaled active wind tunnel are needed to constitute a practical foundation for an atmospheric display[32]. It is also known that combining numerical simulations and physical experiments in order to achieve geometric design of the physical system is a good tool for enhancing the behavior of the wind tunnel systems. This notion is used in developing simplified control laws based on limited sensing and computational resources [32]. Sandip D et al in [32] have showed that the experimental results indicate several physical modifications and unique sensor and control law developments are necessary to achieve controlled wind flow in a physical system. Their results ended up with a conclusion that validating system performance over a wide range of wind speeds and angles serves as a basis for future development of full-scale virtual reality systems with atmospheric display. It is well known that the most famous and important digital controller that carry out most of the information needed to cover both the security and speed all over the tunnels has the upper hand over all other regular ones. It known that there are tremendous numbers of

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researches that have focused on the security and speed issues regarding the wind tunnel systems. These issues are very important during the operation that take place in the tunnels. The security and the speed are the most important factors that must be tackled during studying the flowing of the air turbulence that takes place in the tunnel. The importance of this new field of study will grow as we continue to generate and integrate both analog and digital systems all together. We therefore see a great potential to increase the interaction between both these two systems regarding the speed and security based on intelligent machine learning. Tackling these issues will lead to significant competitive innovation in the field of computers and transportation systems. The efficiency of the security and speed issues raised the need to have an intelligent technique that can merge some of conventional optimal controller to gain both the high speed and security during the usage of tunnels. To start dealing with the dynamical process of the wind tunnel systems and due to the presence of time delay in the mach number [saidah 992], a dynamical representation of an infinite dimensional nonlinear neural networks (NN) with time-delay in the states is developed. This delayed model is transfered to a unique and exact alternative finite dimensional nonlinear generalized state space model with no delays in the states nor in the control input based on the same notion presented in our work in [grid enable I079097]. This unique and exact alternative model [34] is one of the widely adopted closed form sophisticated techniques for solving the presence of time delay element in the state model. It is known that using the interdisciplinary singular systems analysis helped in solving and interpreting the way of dealing with delays elements using closed forms techniques. The importance of this novel method will be used as we continue to obtain real intelligent controllers. A particular active area of research in the field of time delay systems is the application and development of machine learning techniques to design real intelligent controllers. Analyzing large scale systems with time delays in both control and states requires making sense of how to use the unique and exact alternative model developed in [34] to obtain real intelligent controllers for wind tunnel systems. It is well known that the most famous and important digital controller that carry out most of the information needed to cover both the security and speed all over the tunnel systems has the upper hand over all other regular ones. We note that there are tremendous numbers of researches have focused on the security and speed issues in controlling tunnel systems with time delays. These issues are very important during the operation that takes place in the tunnels. The security and the speed are the most important factors that must be tackled during the study of flowing of the air turbulence that takes place in the tunnel. The importance of this new field of study will grow as we continue to generate and integrate both analog and digital systems together. We therefore see a great potential to increase the interaction between both these two systems regarding the speed and security based on intelligent machine learning. Tackling these issues will lead to significant competitive innovation in the field of computers and transportation systems. The efficiency of the security and speed issues raised the need to obtain an intelligent technique that can merge some of the optimal controller to gain both the high speed and security during the usage of tunnel. To start dealing with the design process to obtain a real intelligent controller we need to apply some learning techniques such as neural networks that are widely covered in the literature. Recently, NN have emerged as a powerful tool in pattern recognition, classification and forecasting in many areas. They have featured in a wide range of engineering and industrial journals, often with promising results . Inspired by promising results obtained in other fields, we explored the use of these intelligence techniques for designing a new controller to control wind tunnel systems with delays issues. The main focus of this paper resides in analyzing wind tunnel systems using a computational intelligence techniques such as adaptive NN. The description of a dynamical model of a wind tunnel involving a time delay based on a neural network is introduced in the following section.

2 DESCRIPTION OF A DYNAMICAL MODEL OF A WIND TUNNEL INVOLVING A TIME DELAY BASED ON A NEURAL NETWORK.

This section describes a novel approach for transferring an adaptive NN non linear time-invariant systems having a delay in the states to a unique and exact alternative finite dimensional generalized state space model with no delay in the states nor in the control. This model is capable of generalizing results previously restricted to the non delay systems. The major feature of this new model is its application as a major tool in developing new qualitative properties of linear time-invariant state-delay systems. One of the most practical applications of the generalized model developed is the stabilization process of the wind tunnel model involving a delay in one state. The approach is based on transferring a nonlinear state space system with delayed element to a finite dimensional state space system with neither delays in the state nor in the control to be used in the design of a feedback law which yields a finite eigenvalues, located at an arbitrarily pre assigned value via a realizable transformation. This new transformation gives an easy and direct way to obtain the solution of the delayed control systems in a manner similar to those given for ordinary systems.

It is well known [24] that the presence of time delays in process control problem greatly complicate the analytical aspects of the control system design and make satisfactory design of state apace feedback controller more difficult to implement specially in the field of wind tunnel processes. This complicated processes appeared because controlling the Mach number in test section in wind tunnel is a little difficult due to the unpredictable changes in wind tunnel process dynamics and restriction of air storage volume [12]. Guijun Zhang et al in [12] have described synergistic mechatronics design, sensing, and control of a scaled active wind tunnel. Their studied focused on combined numerical simulations and physical experiments in order to achieve geometric design of the physical system while simultaneously developing simplified control laws using limited sensing and computational resources. Their approach have lacked the analytical treatment in an explicit closed form the effect of the time delay factor that existed in Mach number on the behaviors of the wind tunnel. Instead, they focused their attention on experimental results and ended up with some good physical modifications with unique sensor used with control law in their developments to achieve controlled wind flow in a physical system. On the other hand and as a result of Sandip D et al [32] conclusion, great deals of simulated works have been devoted to the analysis and design of feedback controller schemes for delayed wind tunnel systems among various kinds of delayed systems that occurred in the input controls and/or the state variables.

It is also well known that Saidahmed in [24] has designed a feedback controller of a wind tunnel model involving delays in the states in the regular sense based on the notion of singular system without using the adaptive NNS. Some well known approaches introduced in[12],[32] following similar lines as in [12],[32] reported a full mathematical model of the National Transonic Facility (NTF) which is a continuous-flow cryogenic wind tunnel operating at low temperatures (down to 88.7k) and high Reynold numbers involves a system of nonlinear partial differential equations. The model presented in [12] has shown to be very complicated to be used in the stabilization process in real time and instead a simplified mathematical model of the Mach number dynamic response to guide vane angle changes has been introduced. This mathematical model which has been the subject of many recent investigations [1]-[10] is a system of three differential equations with a delay in one state variable. In [12], a discrete time model is introduced to design a feedback control of the wind tunnel model having delay in the state. Due to the presence of the delay, the dimension of the discrete-time model increases with the decrease of the discretization step size. The approach in [12],[32] is based on splines and approximations of solutions of the infinite-dimensional Riccati-equation which may not be suitable for the wind tunnel model because it requires too much repeated computation when the operating point being changed. Another technique introduced in the literature [1] results in designing a controller whose parameters are functions of the system parameters and the design. parameters (e.g., closed-loop eigenvalues). Although, this method seems to be simple in obtaining the controller parameters, it lakes to have unique controller parameters for specific and desired eigenvalues where the controller can only be numerically implemented. The purpose of this project is to introduce a new approach which based on transferring the mathematical model of the wind tunnel system with delay in the state into a finite dimensional linear system whose dynamical variables have no delays in the states nor in the controls. A distinct advantage of the techniques lies in its simplicity in designing the controller parameters at different operating points in a manner analogous to those given for non-delayed systems and its ability to eliminate the delay element from the state variables. It should also be mentioned that the present technique treats the dynamical behaviors of the system at and after the discontinuity point which occurs at $t=\tau$, where τ is the delay element, much more easy and direct and gives a clear role to estimate and detect such phenomena. This makes it easy to adjust the controller's parameters of linear feedback for systems with state delays to changes in the operating point. It is also shown that the quantitative behaviors of the state- delays systems can be achieved in a manner similar to those obtained for systems without delays where the effect of the time delay are taken into account through the system's parameters. It is our believe that the design procedure proposed in this work is a satisfyingly consistent and useful framework for dealing with system with state-delays, and opens the door to interesting generalizations of results previously restricted to delay-free systems. The major feature of the present technique is shown to be typical for many process control applications and, recently, has been used in designing a new controller for the generalized state space time-delay systems [24]. We note also that the problem of designing a finite dimensional control law for time delay systems has received considerable attention recently in the literature. Qing et al [30] introduces a new process-model control which based on a predictor. This predictor eliminates the time delay from the characteristic equation of the closed loop system. Thus, the design problem for the process with delay can be handled out without taking the delay element into consideration. However, the Smith predictor suffers from some drawbacks such as the cases where the disturbances and non-zero initial conditions are presented in the system, especially in the case where the process has poles in the left half s-plane near the origin. In this case the responses may be sluggish enough to be unacceptable[41]. Another major disadvantages of the smith predictor is that the dimension of the control process should be equal to the dimension of the model beside if the process is unstable then the control process-model needs a new stabilizing control scheme. Many other investigators [30]-[44] introduces alternative design techniques to compensate for the delay effect either by using the state space technique or improving the Smith predictor performance[36]. Since these approaches are heavily based on the main idea of the Smith predictor, then as a result all of them suffer from the essential drawbacks of the Smith predictor, especially in the instability problem of' the process control as well as its dimension. In this paper, we introduce a new novel approach to stabilize linear systems with delayed control which completely avoid using the process-model control. The approach is based on the concept of the state space technique because of its advantages over the other existing technique for improving the system performance. The remarkable feature of the present approach is that its ability to generate the delayed state from the input and the present state of the process. This structure property paved the way by which the major problems of the systems with delayed control can be solved.

3 PROBLEM FORMULATION

So, let us consider the following dynamical wind tunnel neural network involving a time delay in the state variables to identify some wind tunnel applications with some enhancement of those reported in [12],[32] with an addition of a delay factor τ that is included in the state variables. It is known [24] that the dynamic response of the Mach number perturbations δM to small perturbations in the guide vane angle actuator $\delta\theta_A$, in the steady state operating conditions. We consider a dynamical neuron [41]-[44] which is of the form

$$\dot{\mathbf{z}}(\mathbf{t}) = \mathbf{A_1 z(t)} + \mathbf{A_2 z(t-\tau)} + \eta\xi(\mathbf{z}) + \mathbf{B}\ \mathbf{u(t)} \qquad \mathbf{(1)}$$

Where $z\ \varepsilon\ Rn$, n is the state of the neural network, $u\ \varepsilon Rm$ is the input vector , A's and B are matrices of appropriate dimensions, $\eta\ \varepsilon\ R^{nxm}$ is a weight matrix. As it is assumed that the vector field $\theta(z)$: $Rn \longrightarrow Rm$ have the elements increasing monotonically to conclude some information about the original delayed Mach number in wind tunnel system. The elements of this vector field can be presented as sigmoid functions in the form [41]

$$\boldsymbol{\xi_i(z_i) = a_i/(1 + e^{-b_i z_i}) - c_i}$$

Where a_i, b_i, and c_i are i's constant parameters of the function θ to be chosen according to satisfy the back-propagation neural network behavior.

To deal with (1) as a delayed wind tunnel with artificial neural network, we need to know perfect knowledge of the states in the regular dynamical form. Therefore, we first start transferring (1) to its unique and exact alternative form in the standard conventional form by moving the delay element τ from the states to the system parameters[24]. After accomplishing this step and having (1) in its standard state space form with the assumption that no axis to measure the states directly, we next use a modified estimator similar of that reported in [41] to help obtaining the unavailable states by measuring only the output y and the input u of the process in (1). The next theorem is needed to accomplish our proposed model to be put in the standard conventional singular system as follows.

Theorem1: for the linear dynamical model of a delayed wind tunnel with artificial neural network described by (1), there always exit a linear transformation in the form

$w(\tau, s) = e^{\tau s} z(s)$,
where s is a complex plane (usually known as a Laplace algebraic complex plane) that moves the delays element from the state variables to the system parameters of the form

$$\dot{w}(t) = A\,w(t) + \eta\,\xi(z(t)) + B\,u(t) \qquad \textbf{for } 0 \le t \le \tau \qquad \textbf{(2-a)}$$

and

$$F(\tau)\,\dot{z}(t) = \hat{A}\,z(t) + F(\tau)\,(\eta\,\xi(z(t)) + \mathbf{B\,u(t)}) \quad \textbf{for } t \ge \tau \qquad \textbf{(2-b)}$$

It should be noted that the term $\eta\ \theta(z(t))$ is treated similarly as if it would be another input.
With initial value $w(\tau)$ for $t \ge \tau$ is obtained from (2-a) at $t = \tau$ and (2-b) is a unique and exact alternative model of (1) for all $t \ge \tau$ in the form of generalized state space system,

$F(\tau) = I + A2\,A(\tau)$, $A(\tau) = \int_0^\tau e^{-A_1\theta}\,d\theta$,and $\hat{A} = A1 + A_2$

Proof: We prove this theorem by introducing the linear transformation introduced by Saidahmed [5] of the form

$$\mathbf{w(\tau, s) = e^{\tau s} z(s)} \qquad \mathbf{(3)}$$

with initial value $w(0, s)$ is given by
$w(0, s) = z(s)$
By taking Laplace transform of (1) and applying the linear transformation given in (3), results in

$$\frac{dw(\tau,s)}{d\tau} = \mathbf{Aw(\tau,s) + e^{\tau s}z0 + A_1 z(s) + e^{\tau s}(\,P(s) + B\ \ u(t))} \qquad \mathbf{(4)}$$

where $P(s)$ is the Laplace transform of $\eta\,\xi(w(t))$. **Solving (4)** with respect to $w(\tau, s)$, yields

$$w(\tau, s) = e^{A_1\tau}z(s) + \left[\int_0^\tau e^{A_1(\tau-\theta)}d\theta\right] A_2 z(s) + \left[\int_0^\tau e^{A_1(\tau-\theta)}e^{\theta s}d\theta\right](\,P(s) + Bu(s)) + \left[\int_0^\tau e^{A_1(\tau-\theta)}e^{\theta s}d\theta\right]\mathbf{z_0} \qquad \mathbf{(5)}$$

By inspection, we note that the most right hand term of (5) can be rewritten as

$$\left[\int_0^\tau \mathbf{e^{A_1(\tau-\theta)}e^{\theta s}d\theta}\right]\mathbf{z_0} = \mathbf{(sI - A1\,)^{-1}}\left[\mathbf{e^{s\tau}\,I - e^{A_1\tau}}\right]\mathbf{z_0} \qquad \mathbf{(6)}$$

and the third term on the right hand side of (5) can be integrated by part, so we have

$$\left[\int_0^\tau \mathbf{e^{A_1(\tau-\theta)}e^{\theta s}d\theta}\right]\mathbf{(\,P(s) + Bu(s)) = (sI - A1\,)^{-1} * [\,e^{s\tau}\,I - e^{A_1\tau}\,] * (\,P(s) + B\,u(s))} \qquad \mathbf{(7)}$$

Collecting (6) and (7) all together and converting the result into the time domain, we end up with

$$\mathbf{z(t)} = \left[\mathbf{e^{A_1\tau} + \int_0^\tau e^{A_1(\tau-\theta)}A_2\,d\theta}\right] * \mathbf{z(t-\tau)u_s(t-\tau)} \mathbf{+ e^{A_1 t}\,[\,u_s(t) - u_s(t-\tau)]} \mathbf{+ \int_0^t e^{A_1(t-\theta)}(\eta\,\xi(z(t)) + B\,u(t)) * [u_s(t) - u_s(t - \tau - \theta)]d\theta} \qquad \mathbf{(8)}$$

where $u_s(\,.\,)$ stands for a unit step function . It is clear from examining (8) that for $0 \le t \le \tau$, we get

$$\mathbf{z(t) = e^{A_1 t}z_0 + \int_0^t e^{A_1(t-\theta)}(\eta\,\xi(z(t)) + B\,u(t))\ \ d\theta,\ 0 \le t \le \tau} \qquad \mathbf{(9\text{-}a)}$$

Obviously, (9-a) is in the form of the linear differential steady state

$$\mathbf{\dot{z}\,(t) = A1z(t) + \eta\,\xi(z(t)) + B\,u(t), 0 \le t \le \tau} \qquad \mathbf{(9\text{-}b)}$$

and the part of the dynamic system (1) for $t \ge \tau$ with initial value x(τ) can be also obtained from the (8) at $t = \tau$ as

$$\mathbf{e}^{A_1\boldsymbol{\tau}}\boldsymbol{z(t)} = (\boldsymbol{I} + \mathbf{A}(\boldsymbol{\tau})\boldsymbol{A_2})\boldsymbol{z(t-\tau)} + \int_0^t \mathbf{e}^{A_1(\tau-\theta)}(\boldsymbol{\eta}\,\boldsymbol{\xi}(\mathbf{z}(\mathbf{t})) + \mathbf{B}\,\mathbf{u}(\mathbf{t}))\ \mathbf{d}\boldsymbol{\theta} \qquad \mathbf{(10)}$$

Substituting (10) into (1) and collecting similar terms, results in

$$\mathbf{A}(\boldsymbol{\tau})\dot{\mathbf{z}}(\mathbf{t}) = \mathbf{z}(\mathbf{t}) - \mathbf{z}(\mathbf{t}-\boldsymbol{\tau}) + \mathbf{A}(\boldsymbol{\tau})\,(\boldsymbol{\eta}\,\boldsymbol{\xi}\big(\mathbf{z}(\mathbf{t})\big) + \mathbf{B}\,\mathbf{u}(\mathbf{t})),\ \mathbf{t} \geq \boldsymbol{\tau} \qquad \mathbf{(11)}$$

Premultiplying (11) by A_2, using (1) and collecting similar terms, we end up with singular time invariant system of the form

$$\mathbf{F}(\boldsymbol{\tau})\dot{\mathbf{z}}\,(\mathbf{t}) = \widehat{\mathbf{A}}\,\mathbf{z}(\mathbf{t}) + \mathbf{F}(\boldsymbol{\tau})\,(\boldsymbol{\eta}\,\boldsymbol{\xi}(\mathbf{z}(\mathbf{t})) + \mathbf{B}\,\mathbf{u}(\mathbf{t}))\ \textbf{for}\ \mathbf{t} \geq \boldsymbol{\tau} \qquad \mathbf{(12)}$$

Obviously, (12) is in the form of linear dynamical model of a grid computing transactions with no delays factor in the generalized system form which contains the non-delay system as special case see [24] for more information about (12). To see this, let $\tau = 0$ in (12), yields

$$\dot{\mathbf{z}}\,(\mathbf{t}) = \widehat{\mathbf{A}}\,\mathbf{z}(\mathbf{t}) + \boldsymbol{\eta}\,\boldsymbol{\xi}(\mathbf{z}(\mathbf{t})) + \mathbf{B}\,\mathbf{u}(\mathbf{t}) \qquad \mathbf{t} \geq \mathbf{0} \qquad \mathbf{(13)}$$

Eq.(13) shows direct verification of the present approach. It should be mentioned that (12) is also called a unique alternative representation of (1) in the sense that the behavior of the system is uniquely determined by (12). On the other hand and as seen by (9-b), the dynamical behavior of the system for $0 \leq t \leq \tau$ with $\tau > 0$ takes the expected form that can be derived directly from(1) as

$$\dot{\mathbf{z}}\,(\mathbf{t}) = \mathbf{A_1}\,\mathbf{z}(\mathbf{t}) + \boldsymbol{\eta}\,\boldsymbol{\xi}(\mathbf{z}(\mathbf{t})) + \mathbf{B}\,\mathbf{u}(\mathbf{t}),\ \mathbf{0} \leq \mathbf{t} \leq \boldsymbol{\tau} \qquad \mathbf{(14)}$$

Which means, we could have been obtained (14) by inspection from (1) by knowing that $A_2 z(t-\tau)u_s(t-\tau) = 0$ from $0 \leq t \leq \tau$. This strengths theorem (1) and supports the idea that (14) describes completely the behavior of the system (1) for $0 \leq t \leq \tau$. This completes the proof.

It is important to note that, in most practical cases the matrix F(τ) in (12) is invertible and this reduces the difficulty which usually encountered when dealing with states-delay systems. We should also know that in case of having (12) as a singular system it must be checked first for the solvability condition, then (12) can be divided into two essential subsystems: slow and fast subsystems. The slow part contains all the dynamical information about system (1) for $t \geq \tau$ while the fast part involves the impulsive modes due to the existence of the algebraic behavior that occurs only at $t = \tau$.

4 A NEW APPROACH FOR DESIGNING AN INTELLIGENT CONTROLLER OF A WIND TUNNEL INVOLVING A DELAY

Accordingly, the slow part of our general imitation model gives rise to dynamics which fall into a conventional standard class of state space singular models that are considered in evolutionary game theory namely regular, payoff-monotone dynamics. We note that there are various properties of payoff monotone dynamics; where most results focus on the case of single population continuous time dynamics. As it is well known [20], the stability properties obtained for continuous-time dynamics (12) in general do not directly translate to discrete time formulations; because in discrete-time overshooting phenomena might destabilize equilibrium that are stable with respect to corresponding continuous-time dynamics. To see the usefulness of the preceding approach, let us examine the following dynamical model of a wind tunnel with delays in the state as given in [24]. Our attention here will be focused on the effect of the delayed element on the behaviors of the wind tunnel during its dynamical operation interactions and the interested people in wind tunnel systems involving a delay based on an artificial Neural Network are advised to see [20],[42]. The major feature of the present technique is shown to be typical for many process control applications and, recently, has been used in designing a new controller for the generalized state space time-delay systems [24]. It is known from [24] that the dynamic response of the Mach number perturbations δM to small perturbations in the guide vane angle actuator $\delta\theta_A$, in the steady state operating conditions of a wind tunnel systems involving a delay based on an ANN be given by the following applications.

$$\dot{\boldsymbol{z}}(\boldsymbol{t}) = \boldsymbol{A_1 z(t)} + \boldsymbol{A_1 z(t-\tau)} + \boldsymbol{\eta}\,\boldsymbol{\xi}(\mathbf{z}(\mathbf{t})) + \mathbf{B}\,\mathbf{u}(\mathbf{t}) \qquad \mathbf{(15)}$$

where

$$\boldsymbol{A_1} = \begin{bmatrix} -\boldsymbol{a} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} \\ \mathbf{0} & -\boldsymbol{\omega}^2 & -\mathbf{2}\boldsymbol{\zeta\omega} \end{bmatrix}, \quad \boldsymbol{A_2} = \begin{bmatrix} \mathbf{0} & \boldsymbol{ka} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix},$$

$$\boldsymbol{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \boldsymbol{\omega}^2 \end{bmatrix}, \quad \boldsymbol{\eta}\,\boldsymbol{\xi}(\mathbf{z}(\mathbf{t})) = \begin{bmatrix} \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{z}}} - \mathbf{0.5} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix}$$

and $z_1 = \delta M$, $z_2 = \delta\theta$, $z_3 = \delta\theta$, $u = \delta\theta_A$, and δθ the guide van angle, $\tau \geq 0$ is a delay element , a, k, ζ, ω are parameters depending on the operating point and Presumed constant when the perturbation δM, δθ , $\delta\theta_A$,small. For the sake of testing the exactness and uniqueness solution introduced by theorem (1), we introduce the following development based on the application of this new method stated in theorem (1) to deal with (15). We first convert the infinite dimensional time delay system (15) to a finite dimensional linear generalized state space model with no delays in the states nor in the control input. Secondly and based on this new model, we design a scheme of an intelligent feedback controller which yields a fast mach number response, which in turn reduces the cost of liquid nitrogen losses during the transient regimes, can be obtained. To see this and based on theorem (1) , system (15) can be easily transferred to an exact and alternative form for $0 \leq t \leq \tau$ as

$$\dot{\boldsymbol{z}}(\boldsymbol{t}) = \boldsymbol{A_1 z(t)} + \boldsymbol{\eta}\,\boldsymbol{\xi}(\mathbf{z}(\mathbf{t})) + \mathbf{B}\,\mathbf{u}(\mathbf{t}) \qquad \mathbf{(16\text{-}a)}$$

and since F(τ) are invertible for all τ ≥ 0, then (15) for t ≥ τ takes the form

$$\dot{z}(t) = (F(\tau))^{-1}\hat{A}z(t) + \eta\,\xi(z(t)) + B\,u(t)) \qquad (16\text{-b})$$

with

$$F(\tau) = I + A_2 A(\tau),\; A(\tau) = \int_0^{\tau} e^{-A_1\theta}\,d\theta \quad ,\hat{A} = A_1 + A_2$$

Eqs.(16-a) and (16-b) are in the from of conventional state space form and a feedback controller can be easily obtained to stabilize (16) by the proper choice of the feedback gain see [41], [42].

Example1: Let a wind tunnel system be described by

$$\dot{z}(t) = z + z(t-\tau) + \frac{1}{1+e^{-z}} - 0.5 + u(t),\; z(0) = 2.0 \qquad (17)$$

With transmission delay τ = 1, using theorem (1) for 0≤ t ≤ 1, we have

$$\dot{z}(t) = z + \frac{1}{1+e^{-z}} - 0.5 + u(t) \text{ with } x(0) = 2.0 \text{ for } 0 \le t \le 1 (18)$$

Using a nonlinear feed back in the form

$$u = kz - \frac{1}{1+e^{-x}} + 0.5$$

with k= - 2 to stabilize (18), thus we get

$$\dot{z}(t) = -z(t)\,,\quad x(0) = 2.0 \qquad (19)$$

Which has a solution given as

$$z(t) = 2.0e^{-t} \quad ,0 \le t \le 1 \qquad (20)$$

The initial value z(τ) to be used with the second part of theorem (1) for t ≥ τ is obtained from (20) at t = τ =1 as

$$z(1) = 0.736 \qquad (21)$$

The second part of theorem (1) is obtained from (12) for t ≥ 1 which is a unique and exact alternative form of (15) can also be obtained as

$$F(\tau)\dot{z}(t) = \hat{A}z(t) + F(\tau)(\eta\,\xi(z(t)) + B\,u(t)),\quad t \ge 1 \qquad (22)$$

By using $A_1=1$, $A(\tau=1) = A(1) = \int_0^1 e^{-A_1\theta}d\theta, \quad =0.632$, $\hat{A} = 2$, $u(t) = -2 - \frac{1}{1+e^{-x}} + 0.5$, $F(1) = 1 + A_2A(1) = 1.632$, and $\hat{A} = 2$, then (22) reduces to

$$\dot{z}(t) = -0.225\,z(t) \qquad ,t \ge 1 \qquad (23)$$

with initial value z(1) = 0.736, as calculated from (20) at t = τ = 1

It is clear from (23) that the unstable wind tunnel systems with delayed time (17) with a nonlinear controller

$$u = f(kz) = kz - \frac{1}{1+e^{-z}} + 0.5$$

can be stabilized by the proper choice of the nonlinear feedback gain u = f(kz) based on the same technique being used with the conventional state space design approach for controlling the time invariant systems. This results support the effectiveness of our approach introduced in this work. Next we show how to establish trust relationship in networked grid enabled applications systems based on an inelegant technique.

5 ADAPTIVE CONTROL SYSTEM BASED ON SLOW MODE OF THE DYNAMICAL CONSTRUCTION SCHEMA FOR IMPROVING WIND TUNNEL SYSTEMS (WTS)

Recently, It is well known that improving the performance of WTS issues has received considerable attention in the literature[25]-[44]. These issues have been raised due to uncertainty as well as the presence of the delay element in the Mach number control in a wind tunnel. Therefore, we need to build a new rule to be used for constructing dynamical schema relationship among wind tunnel systems. It is well known that the dynamical schema models are not well-suited for dynamic WTS environment, because most applications need to be designed in a real physical environment. To design this kind of dynamical schema, we need to deal with system (2-b) in the regular standard form which can be transformed into two modes : slow and fast as had been reported in Saidahmed [24]. From this work, it is well known that the slow mode of (2-b) takes the form

$$\dot{z}_s(t) = \hat{A}_s(\tau)z_s(t) + \eta_s(\tau)\,\xi_s(z(t)) + B_s(\tau)\,u(t), \text{ for } t \ge \tau \qquad (24\text{-a})$$

$$y_s(t) = C(\tau)\,z_s(t)$$

and the fast mode is written as

$$\tilde{F}(\tau)\,\dot{z}_{f(}t) = \hat{A}_f(\tau)z_f(t) + \eta_f(\tau)\bar{\xi}_f(x_f) + B_f(\tau)u(t) \text{ for } t \ge \tau \qquad (24\text{-b})$$

$$y_f(t) = C(\tau)z_f(t)$$

where all related matrices and variables concerning the subscripts slow and fast modes can be found in more details in [24]. We note from [5] that the fast mode represented in (24-b) vanishes for all t > τ+, therefore, we will focus our attention on (24-a) for designing the proposed dynamical schema of WTS. Since it is assumed that all state variables are not available for direct measurement, then the neural network defined in (22-a) cannot be used directly in the design of an intelligent controller without having all the state available to be measured at hand. Therefore, Using theorem 1 a model free observer may be applied now to get the full-state observation from the output measurement and an adaptive intelligence model to enhance dynamic performance of WTS can be easily implemented [42]. A modified model free estimator reported in[41] can be used to get a full-state estimation from the available output measurements as

$$\dot{\bar{\mathbf{z}}}_s(\mathbf{t}) = \widehat{\mathbf{A}}_s(\tau)\,\bar{\mathbf{z}}_s(\mathbf{t}) + \mathbf{L}\,\mathbf{sgn}\big(\mathbf{y}_s(\mathbf{t}) - \bar{\mathbf{y}}_s(\mathbf{t})\big) - \mathbf{K}\big(\mathbf{y}_s(\mathbf{t}) - \bar{\mathbf{y}}_s(\mathbf{t})\big), \quad \mathbf{t} \geq \tau \qquad (25)$$

$$\mathbf{y}_s(\mathbf{t}) = \boldsymbol{C}(\tau)\mathbf{z}_s\,(\mathbf{t})$$

Where $\mathbf{L} = -\rho P^{-1} C^T$, and **K** is a positive gain matrix, $P = P^T > 0$ (T denotes transposed of a matrix) is a solution of the Lyapunov equation which is related to $\overline{A}$, C, and K, p > 0 is related to C in (25). Then the estimate $\bar{z}$ estimated from (25) is considered as the full-state of the grid computing process and it is utilized to obtain a neural network to identify the WTS model in (1). For More details about the (25) see [Wen Yut]. Based on system (25) and for the sake of brevity, it is an easy task to show that the required proposed dynamical adaptive intelligence model with delayed factor follows similar lines as those reported in [24]. It should be also noted as reported in [41] that this kind of adaptive controller have different categories of the multi-model neuro control that can be summarized and follow similar lines as reported in [20] as follows.

1- For one neural estimator and multiple neuro controllers, the modified neuro identifier adaptive control in terms of the transmission delay τ can be obtained from the sliding mode control as:

$$\boldsymbol{u} = -\boldsymbol{k}\,\mathbf{P}^{-1}\,sgn(\mathrm{e}(\tau)), \quad \mathbf{k} > 0 \quad \mathbf{for} \quad \mathbf{t} \geq \tau \qquad (26)$$

where e(τ) denotes the bounded identification error in terms of the transmission delay τ.

2- For multiple dynamic neural networks controller, the modified neuro identifier in terms of the transmission delay τ takes the form

$$\dot{\bar{\mathbf{z}}}_s(\boldsymbol{t}) = \boldsymbol{A}_{s\sigma}(\boldsymbol{\tau})\bar{\mathbf{z}}_s(\boldsymbol{t}) + \boldsymbol{\eta}_s^{\sigma}(\boldsymbol{\tau})\xi_{\sigma}\big(\bar{\mathbf{z}}\,(\boldsymbol{t})\big) + \boldsymbol{B}_{s\sigma}\,(\boldsymbol{\tau})\mathbf{u}(\mathbf{t}), \mathbf{t} \geq \tau \qquad (27)$$

Where a $\boldsymbol{\sigma}\ \varepsilon\ \mathbf{Z} = \{\mathbf{1}, \mathbf{2}, \ldots, \mathbf{z}\}$ is the switching input.

Both the free time delay multiple neuro controller defined in (26) and the system (27) are said to be intelligent WTS computing adaptive control for all t ≥ τ . First, we need to get a slow model which has no delay element in its variables nor in its control input and then we design a neuro identifier which leads to get an adaptive control system. The first control approach is based on one neuro identifier while the second approach has utilized the notion of multiple neuro identifiers reported in [41] where the uncertainties compensation of the bounded control error uses classical control technique where the bad transient response caused by the single neuro identifier could be overcome.

Since we transferred the dynamical delay time model of wind tunnel based on Neural networks technique defined in (1) to its alternative unique and exact model (2) without delays in the state variables nor in the control input, then all conventional approaches that are reported in the literature can be easily extended to utilize the improvement of WTS. In what to follow we extend some of our works introduced in [20] to develop our proposed time optimization back-propagation neural networks (TOBPNN) algorithm based on the slow part of this alternative model.

6 THE PROPOSED TOBPNN AND SCHEDULING APPROACHES USED FOR WTS

Our work in [20] can be easily extended to cover the computer network of WTS that are geographically distributed based on grid computing techniques. So, We start our work by assuming that all computer controlling each tunnel are connected in parallel processing with both deadline and budget constrained (DBC) algorithms are based on TOBPNN. The time-optimization scheduling algorithm for WTS program uses all the affordable data to process jobs in parallel as early as possible. The aim of the Time optimization scheduling algorithm is to complete the tasks of each computer controls the tunnel as quickly as possible within the available budget. Our proposed scheduling algorithm takes the scheduling decision based on the important information comes from the TRTE Model as shown in Fig. 6.

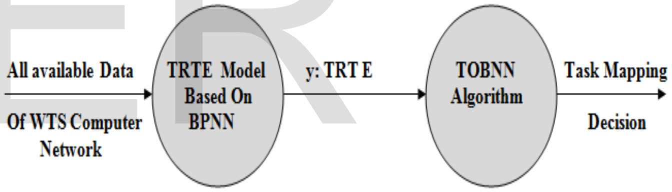

Fig. 6 Scheduling algorithm of WTS Computer Network based on TOBPNN.

Following similar steps that we developed in [20], one can easily implements DBC with time-optimization scheduling algorithms based on TOBPNN by developing a computer control program that has the ability to execute a complete grid computing for WTS based on Java programming language where the proposed scheduling algorithm is encapsulated within the broker scheduling heuristics. In what to follow, we describe how our proposed algorithm works in the compute intensive experiment Gridlets considering only one Gridlet specifications in the experiment. The Gridlet length is determined by the number of million instructions (is measured in terms of MI) and the size of Gridlet input file size and the Gridlet output file size in terms of MB as shown in Table 1.

Table 1 The Gridlet specification

length(MI)	Input file	

Tunnel Name	Baud Rate (Mbit/s)	Max. Simulation Time (hour)	Scheduling Policy	# of Gridlets
Name _1	200	15 hour	TOBPNN	20
Name _2	350	19 hour	Min-Min	300
Name _3	350	12 hour	Cost opt.	100
.....	….	…..	…..	…..
Name _N	240	18 hours	Time opt.	200

	size(BYTE)	Output file size(BYTE)
3035.5	3035.5	80

Applying the information of TRTE Model to the gridlet specification given in table 2 for 5 nodes that are representing all computers connected in the grid for controlling flow movement of the tunnels.

Table 2 The results of applying the proposed T R estimation model

Tunnel's Computer id	Tunnel name	No of PE	Tunnel's Computer Rating(MIPS)	Cost per MI($/MI)	Expected task run time(sec)
10	T4	7	1420	5	728355
20	T2	6	2460	5	728355
30	T0	16	7424	14.5	643435
40	T1	4	2060	50	541720

Feeding the data given in the last column in Table 2 to the proposed TOBPNN scheduling algorithm, we easily obtain least expected task run time as output of the TOBPNN.

7 Results on Simulation Environment of WTS Using Grid Enabled Computing Scheduling Based on BPNN

A simulation grid environment of WTS using grid enabled computing scheduling based on BPNN can be created in a way similar to the general simulation model in GridSim. The tunnel's node data can be created with different Gridlets properties, length, size and different scheduling policies. Table 9.1 shows GridSim properties that are needed to implement a simulation of a task using a Gridlet object.

Table 3 A General Sample Gridlet Object.

Table 3 shows needed data regarding the Gridlets with different requirements. These data as well as defining their number of Gridlets, connection speed (baud rate), maximum time to run simulation, and scheduling policy like Gridsim time optimization(Gridsim TO),TOBPNN, and Min-Min scheduling algorithms. Meanwhile, Table 4 gathering some other required data to be used in the development of TRTE Model which consist of two classes and embedded them in scheduler adviser method in GridSim broker class. Our proposed TOBPNN starts searching to find the most suitable tunnel's node based on the expectation of the task run time in all available tunnels then computes the minimum completion time.

Table 4 User Object needed data.

Gridlet ID	Gridlet Length(MI)	Input File Size (MB)	Output File Size (MB)
1	2956	30	6
2	2478	33	989
3	56873	231	4422
4	76982	447	1000
……	……	…….	……
N	7063	80	200

To conclude our work so far in this paper, we have used GridSim default broker as a tunnel broker. We have created a TRTE Model which consists of two classes and embedded them in scheduler adviser method in GridSim broker class. Then, the TOBPNN tries to find the most suitable tunnel's node based on the expectation of the task run time in all available tunnel then computes the minimum completion time. Finally, the TOBPNN assigns the Gridlet to the found the required tunnel. The computer program creates an experiment that acts as a placeholder before starting the simulation processes where GridletList that stores a set of Gridlets should be processed with tunnel scheduling policy requirements. That means, when simulation process starts, the broker creates a tunnel list to store dynamic information and characteristic properties of available tunnel acquired from the GIS. During the simulation each broker continuously queries the GIS and gets dynamic information about the available tunnel and starting loading them. Then Tunnel's node sends its query to its tunnel broker via the application interface. The broker of each tunnel gets their Gridlets from its experiment object via experiment interface of that broker. After that the broker of tunnels puts all Gridlets to be sent for execution into the unfinished GridletList. In our design, it is no necessary to get time management (i.e. each tunnel wait specific delay and then sends all Gridlets at one moment packed in experiment object to its brokers), because the delay factor has been already overcome using theorem (1). This delay is defined when the tunnel's node is created. Based on theorem (1) , A new Gridlet during the simulation can be developed with a dynamic scheduling algorithm. That means new tunnel inquiry can send new

Gridlets until this simulation finishes.

The Grid Economic tunnel's broker with its components is introduced next. The proposed Time Optimization based on Back-Propagation neural network (TOBPNN) scheduling algorithm is also discussed. To show the usefulness and effectiveness of the two proposed scheduling algorithms, their results are compared with the bench mark min-min[40] scheduling algorithm and the GridSim time optimization (GridSim TO)[24].

8 SIMULATION RESULTS AND ANALYSIS

In this section, we used the GridSim toolkit to simulate a Grid environment and a Nimrod-G like deadline and budget constrained scheduling system called economic Grid resource broker. The simulated Grid environment contains tunnel's nodes model and their entities with different requirements. The operators create an experiment that contains a tunnel's node model application specification (a set of Gridlets that represent application jobs with different processing) and quality of service requirements (deadline and budget constraints with optimization strategy). We created two entities that simulate users and the brokers by extending the GridSim class. When simulated, each user entity having its own application and quality of service requirements creates its own instance of the broker entity for scheduling Gridlets on resources. In this section, we also discuss the results of implementing scheduling algorithms such as the proposed TOBPNN, Min-Min and GridSim TO in grid environment. The detailed performance evaluation of economic driven scheduling algorithms is carried out through a series of simulation scenarios by varying deadlines, budgets, the number of gridlets in the experiment, optimization strategies and simulating geographically distributed Grid. Our work is applied to the case of virtual grid environment. In order to evaluate the effectiveness of the proposed algorithm we compared its results with other approaches that are well known in the field of grid computing scheduling.

9 SIMULATION PROCESS OF TUNNEL'S NODES MODELING

In order to develop, test, and evaluate the proposed algorithm, a Grid Scheduling Framework for tunnel's nodes is created. This framework consists of: tunnel's nodes model, application model, and scheduling policy. Firstly, in the tunnel's nodes model, it is described as one entity where the a virtual world grid environment with different number and types of tunnel's nodes is simulated. We present a table that contains the used tunnel's nodes model characteristic. The tunnel's nodes model application is modelled as a BoT (Bag-of-Task) where BoT applications are those applications composed of various tasks that are independent on each other. Finally, the scheduling policy defined as TOBPNN is also developed for a bag-of-tasks application to be scheduled on tunnel's nodes model connected through Grid Computing environment. Simulating application scheduling in GridSim environment requires the modelling of GridSim tunnel's nodes model and their applications. The application must be simulated as a set of independent Gridlets (jobs) to be submitted to the grid tunnel's nodes model.

9.1 APPLICATION MODELING

We model a task tunnel applications [20],[22],[24] which have a number of Gridlets that varies from 1 to 5 with a step of 1. In GridSim, these jobs are packaged as Gridlets. Each Gridlet content includes job length in MI, size of job input and output data in mega bytes along with various other execution related parameters. The job length is expressed in terms of the time it takes to run on a standard tunnel resource PE with SPEC/MIPS rating of 100. Scheduler flow manager is an important component of the Economic Resource Broker. It contains the implementation of many scheduling algorithms and heuristics that can be used by the operator to schedule his tunnel application (Bag of tasks) according to his demand. The operator is responsible for submitting his tunnel application and choosing his broker entity. Each user has his own tunnel broker (scheduler) according to his needs and his desired scheduling policy. The operator may need to optimize the time, the cost, time and cost, or no optimization at all. Towards the goal of optimizing the tunnels need we developed and proposed a Time optimization scheduling algorithm based on back propagation neural networks (TOBPNN). Tasks total completion time and throughput are optimized using the proposed scheduling algorithm. The proposed scheduling algorithm is based on estimating tasks run time using back-propagation neural networks. This estimation is evaluated on all available tunnel applications. The tasks are scheduled for the tunnel that gives the minimal task run time. We repeat scheduling until all tasks are finished.

9.2 VIRTUAL WORLD GRID ENVIRONMENT

In this section we first working with virtual grid environment that consists of 5 tunnel's nodes connected to grid computing that are not found in the real world. Many simulation processes are implemented in this environment by varying the number of tunnel's nodes (to be 1, 2, 3, 4, and 5 tunnels) that are geographically distributed and can be treated as resources characteristics in the grid computing networks. Computing algorithms with different number of tunnel's nodes works as Gridlets (jobs) are submitted to each virtual grid environment. The number of tunnel's nodes connected to the Grid in each Computing algorithms varies from 1 to 5 with a step of 1. In each simulation process, we consider the tunnel's nodes characteristics table as shown in table 9.3. The Tasks total completion time and spent budget are measured for the three scheduling algorithms: Min-Min, GridSim TO and the proposed TOBPNN. The percentage improvement of the total completion time among the scheduling algorithms is also plotted. We also noted that, the throughput is measured to show the effectiveness of changing the deadline on the real time jobs(jobs that need to be completed within a specific deadline). The throughput (Gridlet Completion rate) is measured in the simulation process having tunnel's nodes connected to grid networks. The chosen number of tunnels is chosen to be around the number of tunnels in real world wide grid which is almost 5.

9.3 SIMULATION PROCESS USING FIVE CONNECTED TUNNEL IN THE GRID COMPUTING NETWORKS

In this simulation process, 5 tunnel's nodes connected to grid computing network are simulated as a virtual world grid. We randomly choose the tunnels characteristics as shown in Table 5. The results of the submission are summarized in the performance evaluation table as shown in Fig.7. In Fig. 8 , the comparison among the three scheduling algorithms: the Min-Min, the GridSim TO, and the proposed TOBPNN in terms of Make span (Total completion time). Fig.8 illustrates the percentage improvement in minimizing the total completion time. This Figure helps us to make the analysis of the obtained results.

Table 5 Tunnels Characteristics using 5 Tunnel's nodes

Tunnel Name	No. Of processors used in Tunnel's Computers	Rating MIPS	Cost per MI ($/MI)
Tunnel_1	**6**	**534**	**0.11234556**
Tunnel _2	**8**	**1144**	**0.61237865**
Tunnel _3	**4**	**522**	**0.12435422**
Tunnel _4	**2**	**170**	**0.10034012**
Tunnel _5	**10**	**2442**	**0.18794653**

Table 5 summarizes the results obtained after using the three Table scheduling algorithms: Min-Min, GridSim TO, and TOBPNN. Since we are focusing on the time optimization, Fig.7 shows the performance evaluation in terms of total completion time for the Min-Min, GridSim TO, and the proposed TOBPNN scheduling algorithms. In this simulation process, a relative deadline is used so the tunnel's nodes Gridlets completion rate (Throughput) is 100% which means that all tunnel's nodes Gridlets are completed within the specified deadline. When the deadline is greater than the time required to execute all Gridlets consisting of tunnel's nodes, the throughput is not necessarily to be measured. We need to measure the total completion time (make span) and the spent budget for the comparison between the proposed scheduling and other pre-existent approaches.

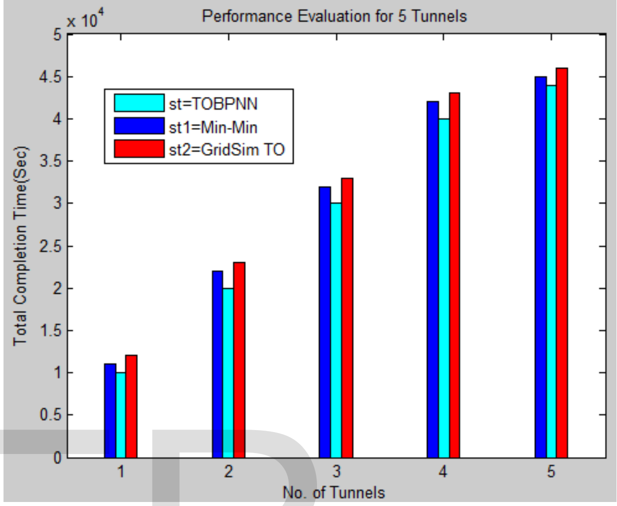

Fig. 7 Total completion time for 5 Connected Tunnel in the computer grid applications

Fig.7 showed that the proposed TOBPNN scheduling algorithms is better than those given by both the benchmark min-min [47] and GridSimTO [8] scheduling algorithms. Two Figures are used to plot the percentage improvement: the first one depicted in Fig.8 shows the percent improvement in the total completion time between the proposed TOBPNN and the Min-Min scheduling algorithms , while the second one given in Fig.9 shows that the percentage improvement between TOBPNN and GridSimTO. We note also that the percentage improvement in total completion time using both Min-Min and TOBPNN scheduling algorithms is measured and calculated using the following relation given in [45]:

Percent improvement = (TCM min-min - TCMTOBPNN) / TCM min-min *100 (28)

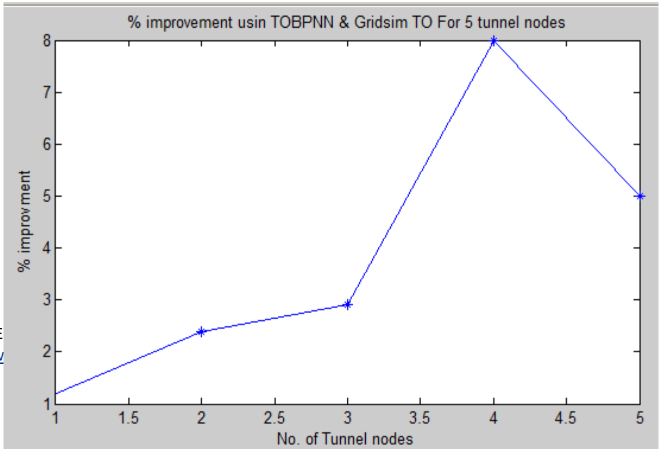

Fig. 8 Percentage improvement between TOBPNN and Min-Min

Fig.8 and Fig.9 indicate that the percentage improvement in (28) tends toward zero when the tunnel's nodes are less than or equal to 2 tunnels. On the other hand, when the number of tunnels increased beyond 3, the percentage improvement sometimes tends to reach 10%. This is because our proposed algorithm made the decision of using low tunnels numbers with maximum processing rate. Also, Fig.9 shows that, especially, when the number of tunnels is greater than 5, the percentage improvement tends to decrease again and my goes to toward zero for large number of tunnels. This is because both the proposed TOBPNN and Min-Min scheduling algorithms make use of same scheduling decision. The percentage improvement in the total completion time between TOBPNN and the GridSim TO scheduling algorithms is almost varying from 1,2% to 8%. This indicate that our proposed algorithm gives better performance other that the GridSim TO especially when the number of connected tunnels are increasing as shown in Fig. 9. In Fig.10 , one can easily sees that the spent budget for the proposed between TOBPNN and the GridSim TO. The Spent budget is measured in terms of $/MI where minimum means the total completion time while the maximum indicates the spent budget.

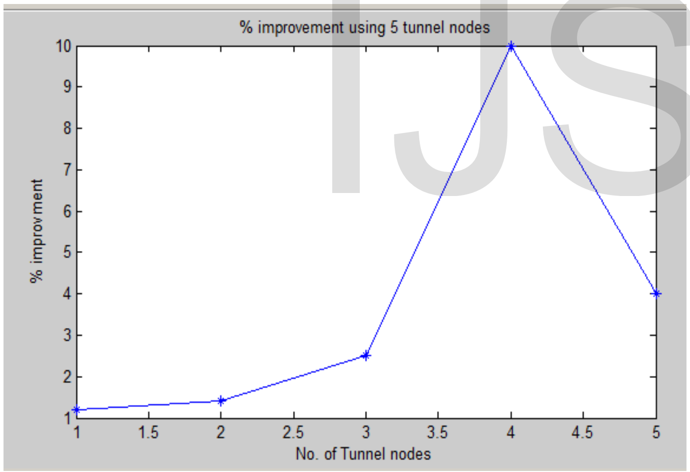

Fig. 9 Percentage improvement between TOBPNN and GridSim TO.

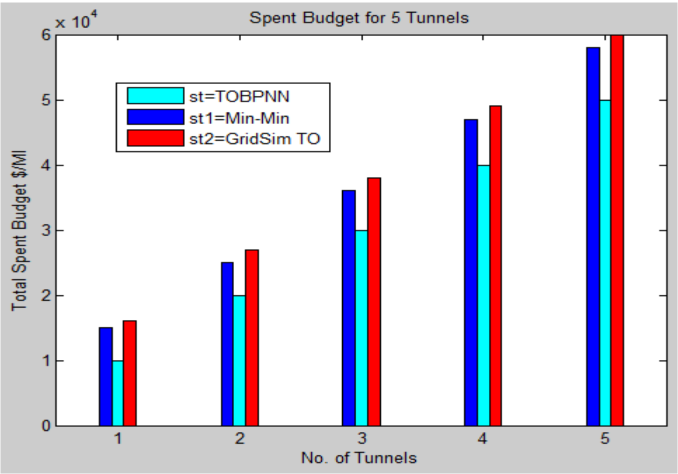

Fig.10 Total Spent budget in the case of using 5 Tunnel's nodes

10 CONCLUSION

This paper introduced the problem of improving the security and performance of wind tunnel systems based on a novel intelligent technique based on a grid computing systems. The paper tackles this problem by first introducing a dynamical platform model that was shown to be suitable for this kind of tunnels platforms to cope with the presence of delays element in the Mach number. This platform had been used to design an intelligent adaptive controller which was easily implemented on overlay computer controlled networks without extra cost. Including the dynamical delay factor in the process has strengthen our work based on a new novel approach that helped in improving the stability and robustness of the flowing objects in the tunnels as well as overcoming many drawbacks issues that appeared in securing the tunnels. The control process that uses the grid computing network to control all tunnels connected to this network involved a dynamical delayed time elements. We showed that both of delays elements and the heterogeneity of the tunnels behaviors are treated using some innovative technique that has led to improve the performance of tunnels which have shown to be faster than previous techniques in terms of the number of tunnels end heterogeneity of their locations . The work has also shown that nonlinear time-invariant systems having a delay in the states can be transferred to a unique and exact alternative finite dimensional generalized state space model with no delay in the states nor in the control input. This model was capable of generalizing results previously restricted to the non delay systems. The major feature of this new model has been considered as an excellent application for dealing with the development of wind tunnel's behaviors and also as a major tool in developing new qualitative properties of linear time-invariant state-delay systems. One of the most practical applications of the generalized model developed is the stabilization process of the wind tunnel model involving a delay in the states. It has been shown that the transient response of such system can be improved by using only one feedback control law, which can be easily implemented in a manner analogous to those obtained for standard state space systems, using the non-delay state variables. The results obtained are much more direct and the presence of time delay in the Mach number dynamics in wind tunnel model does not result in any problem in designing the controller compared with those given by other methods, mainly because the present design procedure has allowed possible updating of the controller's parameters online with the change of the operating point without using any kind of numerical approximation. The result obtained has been used to design a novel intelligent model based on grid computing techniques that enhanced the performance of wind tunnel systems involving a delay. The grid computing that has been used to control the flowing of tunnel's moving objects has been greatly used to obtain the minimal execution time as well as the minimal cost budget. The qualitative performance analysis was easily studied using these dynamical models for implementing a new intelligent adaptive algorithm that has improved sources access through controlling some of their tunnel's nodes using an intelligent grid enabled applications networks models. These models have been achieved based on an object-oriented toolkit, called GridSim, for tunnels modeling and scheduling simulation. GridSim simulates time-and space-shared tunnel's nodes with different capabilities, time zones, and configurations. It supports different tunnels application models that can be mapped to tunnel's nodes for execution by developing simulated tunnel schedulers. This GridSim toolkit simulation package has been considered as the best popular simulation package in this field. This package has helped us in obtaining the best improvement of the required shortest path including the effect of Mach delays, where the performance of tunnel's movement based on grid computing toolkits have been greatly improved. The great achievement in this work has been obtaining a new treatment of the presence of Mach number delays where all delayed elements have been completely removed to the system's parameters that has led to get the most minimal time evaluation algorithms based on Fuzzy decision approach. Based on this now model we demonstrated also that the use of this unique and exact alternative model has adopted closed form techniques for solving the issues of the presence of delays elements in most real tunnel's nodes based on a computer programming using a grid computing technique. The technique introduced has shown to support and improve the quality of control system. This work presents also the advantages of an application of this unique and exact alternative model on the tunnel's nodes using a grid computing involving a delay in one state to have computational intelligence techniques such as Neural Networks (NN) in the design of real intelligent controllers. The results obtained so far presents how to use the technique introduced in this work to improve the performance of the proposed tunnel's nodes involving a delay in one state where a good controller has been tested to have an intelligent control technique to enhance the dynamic performance of tunnel's moving objects. Finally, The results obtained indicate that the performance of the alternative delay models is much better compared to the delayed models in terms of the qualitative behaviors where our final results in the proceeding work has focused on finding a model that combines more than one control technique to achieve common standards control technique with finite order to have an adaptive intelligence model to enhance dynamic performance of tunnel's moving objects based on a grid computing approach. A new optimal back propagation neural network (OBPNN) algorithm has been developed based on grid computing. Some other researches worked on other controllers that concerned with speeding up the flow of air and pay little attention to the security issues. We also introduced the results of budget spent which showed that it is high in our proposed to TOBPNN because it uses tunnel's nodes that give the minimum completion time regardless the processing cost as long as the spent budget still within the available budget. This research has also integrated some of the distinctive controller with a distinct digital program controller that give the tunnels operators all the information about the conditions inside the tunnel through digital display systems to avoid any disturbances that could occur to the moving objects when using these tunnels. This proposed technique has lead to reach the ultimate beneficiary of our goal through using the well known Neuro technique to design a novel intelligent controller. In order to reach this goal the research in this work also has focused on studying an inelegant adaptive controller that can be used to improve the security and the speed that are essential for moving objects through the tunnel systems. To achieve our goal the latest techniques in artificial Intelligence as well as BPNN, functional Networks have been implemented in this paper. Conventional artificial intelligent (AI) techniques has also been used to compare the results and to check the degree of improvement that can be obtained from the proposed controller to gain both the high speed and security during using these tunnels. The usefulness and validity of the presented approach have been shown and examined by numerical examples using GridSim Toolkit with some other famous techniques and based on adaptive intelligent model representing the simulation process of wind tunnels systems involving a delay and connected through a unified grid computing network. It has been shown that a good improvement in the tunnel's performance has been obtained. This improvement was due to the fact that the proposed algorithm takes into account the slow mode of the dynamical model that include the delay element into the model's parameters.

REFERENCES

[1] Ben Yamin R., Yaesh I. and Shaked U.,"Simple adaptive PI control for linear time-delay systems, "8th IFAC Workkshop on Time-Delay Systems, Sinaia, Romania, Sep. 1-3, (2009).

[2] B. Kristiansson', B. Lennartson "Robust PI & PID Controllers including Smith Predictor Structure" Proceedings of the American Control Conference, Arlington, VA June 25-27, 2001.

[3] Boyd S., Ghaoui L. El, Feron E. and Balakrishnan V." Linear matrix inequality in systems and control theory, SIAM Frontier Series , (1994).

[4] Chi-Cheng Cheng, et al., "Predictive Control with Enhanced Robustness for Precision Positioning in Frictional Environment", IEEE/ASME Trans. on Mechatronics, Vol.7, No. 3 : 385 - 392, 2002.

[5] Cosic D., Loncaric S., Rule-based labeling of CT head image. Lecture Notes in Artificial Intelligence, Berlin, Germany, Springer-Verlag, 1999, vol. 1211, 453–456.

[6] Cortes, C., & Vapnik, V., "Support-vector networks. Machine Learning, 20(2), pp. 273–297, 1995.

[7] Dario Bauso, Laura Giarre and Giovanni Neglia, "About the Stability of Active Queue Management Mechanisms " Proceeding of the 2004 American Control Conference, Boston, Massachusetts, June 2004.

[8] Fridman, E., Shaked, U. (2002) A descriptor system approach to H∞ control of linear time-delay systems, IEEE Trans. Automat. Contr., (47), pp. 253-270.

[9] Fridman, E., Shaked, U. (2002) On delay-dependent passivity " , IEEE Trans. Automat. Contr, (47), pp. 664-669.

[10]Feng-Sheng Wang "Adaptive root-locus control for siso processes with time delays ",Optimal Control Applications and Methods, Volume 11, Issue 3, pages 211–221, July/September 1990.

[11] G.-B. Huang and C.-K. Siew, "Extreme Learning Machine with Randomly

Assigned RBF Kernels,” Int’l J. Information Technology, vol. 11, no. 1, 2005.

[12] Guijun Zhang, Tianyou Chai and Cheng Shao,” A Synthetic Approach For Control of Intermittent Wind Tunnel, Proceedings of the American Control Conference, Albuquerque, New Mexico June 1997.

[13] Gahinet, P., Nemirovski, A., Laub, A.J. and Chilali, M. “ LMI Control Toolbox for Use with MATLAB., The Mathworks Inc., 1995.

[14] H. Choe and S. H. Low, "Stabilized Vegas," in Advances in , Communication Control Networks, Lecture Notes in Control and Information Sciences, S. Tarbouriech, C. Abdallah, and J., Chiasson, Eds. New ork: Springer Press, 2004.

[15] Ho-Seop Jeong; Chong-Won Lee; Time delay control with state feedback for azimuth motion of the frictionless positioning device This paper appears in: Mechatronics, IEEE/ASME Transactions , Issue Date: ,Volume: 2 Issue:3 , On page(s): 161 – 168, Sep 1997.

[16] J. Huang, Member, IAENG, T. C. Kuo, Member, IAENG, and H. Y. Tseng “Fuzzy Estimator Design for the Control Systems with Unknown Time-Delay “Proceedings of the World Congress on Engineering 2007 Vol I , WCE 2007, July 2 - 4, 2007, London, U.K.

[17] J.S Jiang, H. Zhang “Full Bayesian Network Classifiers, “Proceedings of the 23 rd International Conference on Machine Learning, Pittsburgh, PA, 2006.

[18] Jian-Xin Xu, and Wen-Jun Cao, "Synthesized Sliding Mode and Time Delay Control for a Class of Uncertain Systems", Automatica 36 : 1909 - 1914, 2000.

[19] Lih-Chang Lin and Ju-Chang Lai , “Stable Adaptive Fuzzy Control with TSK Fuzzy Friction Estimation for Linear Drive Systems “journal of intelligent & robotic systems, vol38 # 2, pp 237-253, september2011.

[20] Mosleh M. Al-Harthi, Hatim Ghazi Zaini , Mohamed T. Faheem,” Adaptive Intelligence Model to Enhance Dynamic Performance of Grid Enabled Applications,” International Journal of Scientific & Technology Research (IJSER), VOL4, ISSUE 2, 2013.

[21] Mahmoud M. Fahmy, Mohammed T. Faheem , TarekE. El-Tobely, SaadM. Hewaidy,” Application of Adaptive- Neuro Fuzzy Inference System on Modeling and Controlling Power Plant” 19th Intr. Confer. On Computer Theory& Applications ICCTA 2009, 17-19 October 2009, Alex. Egypt.

[22] M. Faheem, et al ,” Grid Computing Scheduling Based on Neural Networks,” IJICIS, Vol.11,No.2,July 2011.

[23] M. Stojic and M. S. Matijevic, “A robust smith predictor modified by internal models for integrating process with dead time,” IEEE Trans. Automat. Control, vol. 46, pp. 1293-1298, 2001.

[24] M.T.F. Saidahmed, ” A New Approach for Designing a Feedback Controller of a Wind Tunnel Model Involving a Delay ,” , Proc. Of the 35th Midwest Symposium on Circuits & Systems, 9-12 Aug., 1992 , Washington DC,USA.

[25] Niculescu, S. I., Lozano, R., “On the passivity of linear delay systems “, IEEE Trans. Automat. Contr.

[26] Nauck, D., “Data Analysis with Neuro-Fuzzy Methods”, Habilitation Thesis, University of Magdeburg, 2000.

[27] Provost, F. J., & Domingos, P., “Tree induction for probability-based ranking” Machine Learning 52(3), pp.199-215, 2003.

[28] Pyung Hun Chang, and Suk Ho Park, "On Improving Time Delay Control under Certain Hard Nonlinearities", Mechatronics, Vol.13: 393 - 412, 2003.

[29] P. H. Chang and S. J. Lee, "A straight-line motion tracking control of hydraulic excavator system ”. echatronics, 12(1), 119-138, 2002.

[30] Qing-Chang Zhong’ Robust Control of Time-delay Systems’ Springer-Verlag , London Limited 2006.

[31] Ramalingam, V., Palaniappan, B., Panchanatham, N., & Palanivel, S, “Measuring advertisement effectiveness – a neural network approach”, Expert Systems with Applications, 31(1), 2006.

[32] Sandip D. Kulkarni, et al,” Design, Sensing, and Control of a Scaled Wind Tunnel for Atmospheric Display,” IEEE/ASME Transactions on Mechatronics, Vol. 17, No. 4, Aug. 2012.

[33] S. Ryu and Ch. Cho, “PI-PD-controller for robust and adaptive queue management for supporting TCP congestion Control “ IEEE Computer Society , Proceedings of the 37th Annual Simulation Symposium (ANSS’04), 2004.

[34] S.-U. Lee and P. H. Chang, "Control of a heavy-duty robotic excavator using time delay control with integral sliding surface," Control Engineering Practice, vol. 10, pp. 697-711, 2002.

[35] S. -I. Niculescu, Delay effects on stability. A robust control approach (Springer - Verlag: Heidelberg, LNCIS, vol., 269, May 2001.

[36] S. Majhi and D. P. Atherton, “Automatic tuning of the modified Smith predictor controllers,” in Proc. IEEE, Decision and Control, Sydney, Australia, pp. 1116-1120, 2000.

[37] S.-I. Niculescu and A.M. Annaswamy, “A Simple Adaptive Controller for Positive- Real Systems with Time-delay,” ,Proceedings of the 2000 American Control Conference, Chicago, IL, July 2000.

[38] T. C. Hsia and L. S. Gao, "Robot Manipulator Control Using Decentralized Linear Time-Invariant Time-Delayed Joint Controllers" , In: Proceedings of IEEE International Conference on Robotics and Automation, 2070–75, 1990.

[39] Wang, L. “Adaptive Fuzzy System and Control: Desing and Stability Analysis”, Prentice-Hall, Inc., Englewood Cliffs, New Jersey 07632, 1994.

[40] Wang, F.-S. “Adaptive root-locus control for siso processes with time delays”, Optimal Control Applications and Methods , Volume 11, Issue 3, pages 211–221, July-September 1990.

[41] W. Yut and X. Lit, “Adaptive Control with Multiple Neural Networks”, Proceedings of the American Control Conference Anchorage, AK May 8-10,2002.

[42] X. Xu, L.M. Wan, X.L. Wang, L.K. Wang and Y.C. Liang,” A Time Delay Neural Network for Dynamical System Control,” 2008 IEEE Int.Conf. on Fuzzy Syst. (FUZZ 2008).

[43] Yamin, R. Ben; Yaesh, I.; Shaked, U “Robust simple adaptive control for delayed measurements systems Time Delay Systems,” Volume # 9 | Part# 19th IFAC Workshop on Time Delay Systems (2010), Czech Republic.

[44] Youcef-Toumi, K., and Ito, O., "A Time Delay Controller for Systems with Unknown Dynamics", Trans. ASME, Journal of Dynamic Systems, Measurement, and Control, Vol. 112 :133 -142, March 1990.

[45] Buyya,R., et al," An Economy Driven Resource Management Architecture for Global Computational Power Grids", Proceedings of the 2000 Int. Conf. on Parallel and Distributed Proc. Techniques and Applications (PDPTA 2000), pp. 517-525, June 26-29, 2000, Las Vegas, USA,CSREA Press, USA, 2000.