DEVELOPMENT OF DATA-DRIVEN CONTROLLER FOR SLOSH SUPPRESSION IN LIQUID CARGO VEHICLES

MOHD FALFAZLI MAT JUSOF, MOHD ASHRAF AHMAD, RAJA MOHD TAUFIKA RAJA ISMAIL, MOHD HELMI SUID, MOHD MAWARDI SAARI

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Fakulti Teknologi Kejuruteraan Elektrik dan Elektronik

Universiti Malaysia Pahang

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Abstract

Recently, with the rapid growth in science and engineering, most of the real world process plants have been built on a large scale and complex systems. As a consequence, modeling of such systems may become very difficult and require a lot of effort. Therefore, it is necessary to develop a control method that does not depend on plant models, which is known as the data-driven control approach. At the same time, it is also worthy to consider an optimization tool for the data-driven approach that is simple to understand for engineers and can optimize a large number of control parameters in a fast manner. So far, there have not been enough literatures to discuss the application of data-driven control schemes for the above demands.

Motivated by the above background, a data-driven control scheme is considered in our study. Here, a Safe Experimentation Dynamics (SED) algorithm is suggested as a promising tool for the data-driven control approach. Then, this research report focuses on assessing the effectiveness of the SED-based algorithm for data-driven proportional-integral derivative (PID) control tuning in liquid slosh problems. Slosh or oscillation of liquid inside a container often occurs in many cases, such as, vehicles or ships with liquid cargo carriers, molten metal industries, which is dangerous to handle by the operator. Moreover, sloshing of fuel and other liquids in moving vehicles may cause instability and rollover of the vehicle. For the past decades, various control strategies of liquid slosh motion are based on model-based control schemes. Nevertheless, these methods are difficult to apply in practice. The main reason is that their control schemes do not accurately consider the chaotic behaviour of slosh and the complex fluid dynamic motion in the container. Therefore, a data-driven approach will be more attractive.

In this research project, we propose a data-driven PID controller design based on SED for controlling liquid slosh. The effectiveness of the proposed data-driven PID based SED is evaluated in terms of liquid slosh reduction, tracking performance, and computation time. In addition, the performance of the SED based methods is compared to the other stochastic optimization based approaches, such as Simultaneous Perturbation Stochastic Approximation (SA) and Simulated Annealing (SA). In this study, a real experimental rig of liquid slosh plant is considered to validate the effectiveness of our proposed scheme. In

particular, we develop our own liquid slosh model from the input-output data of real plant through the system identification method. Then, the proposed data-driven PID based SED is applied to the developed model. The outcome of this study has shown that the SED based method is successfully produced better control performances as compared with other stochastic methods. In particular, the proposed data-driven PID scheme can produce slightly minimum liquid slosh motion while maintain the input tracking of the trolley position.

Abstrak

Sejak akhir-akhir ini, dengan perkembangan pesat sains dan kejuruteraan, kebanyakan sistem proses dunia sebenar dibina dalam skala yang besar dan kompleks. Akibatnya, pembinaan model sistem tersebut mungkin akan lebih sukar dan akan mengambil usaha yang lebih untuk disiapkan. Oleh itu, adalah menjadi keperluan untuk membangunkan kaedah kawalan yang tidak bergantung pada model system yang terkenal sebagai kaedah kawalan bebas model. Pada masa yang sama, adalah berbaloi untuk mengenalpasti kaedah pengoptimuman untuk kaedah kawalan bebas model yang mudah difahami oleh juutera-jurutera dan boleh menoptimumkan bilangan parameter kawalan yang banyak dalam masa yang pantas. Setakat ini, masih kurang lagi literatur yang membincangkan aplikasi kaedah kawalan bebas model untuk keperluan di atas. Bermotivasi dari latar belakang di atas, satu skim kawalan bebas model telah dikenalpasti dalam kajian kami. Di sini, algoritma eksperimen dinamik selamat telah dicadangkan sebagai alat pengoptimuman yang terbaik untuk skm kawalan bebas model. Seterusnya, kajian ini lebih berfokus kepada penilaian keberkesanan algoritma pengganggaran rawak gangguan serentak untuk penalaan kawalan perkadaran-pengkamiran-pembezaan (PID) bebas model dalam masalah kocakan cecair. Kocakan ataupun getaran cecair dalam kontena selalunya berlaku dalam banyak situasi, iaitu, kenderaan atau kapal yang membawa muatan cecair, industri cairan besi, yang mana berbahaya kepada pengendali ataupun pekerja. Tambahan pula, kocakan cecair minyak dan cecair lain dalam kenderaan bergerak boleh menyebabkan ketidakstabilan dan menterbalikkan kenderaan tersebut. Sepanjang beberapa dekad yang lepas, pelbagai strategi kawalan kocakan cecair adalah berdasarkan skim kawalan berasaskan model. Walaubagaimanapun, kaedah-kaedah ini adalah sebenarnya sukar diaplikasi untuk sistem sebenar. Justifikasi utama adalah kerana skim kawalan mereka tidak secara tepat mengenalpasti ciri-ciri sebenar kocakan air dan kerumitan pergerakan dinamik cecair tersebut didalam kontena. Oleh itu, kaedah kawalan bebas model adalah sangat menarik untuk dicuba. Dalam kajian ini, kami mencadangkan satu kawalan PID bebas model berasaskan eksperimen dinamik selamat untuk mengawal kocakan cecair. Keberkesanan cadangan kaedah kawalan PID bebas model berasaskan SPSA dinilai dari segi pengurangan kocakan cecair, prestasi penjejakan dan masa komputasi. Sebagai tambahan, prestasi kaedah berasaskan SED dibandingkan dengan kaedah berasaskan pengoptimuman yang lain, seperti SPSA dan SA. Dalam kajian ini, peralatan eksperimen sebenar kocakan cecair telah digunakan untuk menentusahkan

keberkesanan kaedah yang dicadangkan. Secara terperinci lagi, kami telah membangunkan model kocakan cecair berdasarkan data input dan output daripada system sebenar melalui kaedah system pengecaman. Seterusnya, kaedah kawalan PID berasaskan SED diaplikasi terhadapa model yangtelah dibangunkan. Hasil daripada kajian telah menunjukkan bahawa kaedah-kaedah berasaskan SED telah berjaya menghasilkan kawalan prestasi yang lebih baik berbanding kaedah yang lain. Secara lebih jelas, cadangan skim kawalan PID bebas model boleh menghasilkan kocakan cecair yang minimum dan dalam masa yang sama mengekalkan penjejakan posisi troli yang membawa cecair tersebut.

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Chapter 1

Introduction

1.1 Background and Research Motivation

1.1.1 What is data-driven controller design?

Data-driven controller design is to find a controller using the input-output (I/O) data of the systems, which are controlled tentatively, but without using explicit or implicit information of the plants such that the performance of the control objective is achieved. The conceptual structure of the data-driven controller is described in Figure1.1. For example, the control objective is evaluated in terms of the minimization of the measured error and input of the controlled system, and minimization or maximization of the measured output (e.g., minimization of the fuel consumption, maximization of the power production). The control performance value of the given evaluation period is then used by the optimization tool to obtain an updated tuning value for the controller at the next iteration. This tuning process is iteratively performed until the final iteration.

The significant feature of this method is that both controller design and control system analysis are simultaneously performed based on the measured I/O data. In addition, since the controller is designed without using the plant model, this method can directly handle a large class of plants (possibly nonlinear) as long as the required measurement data is available.

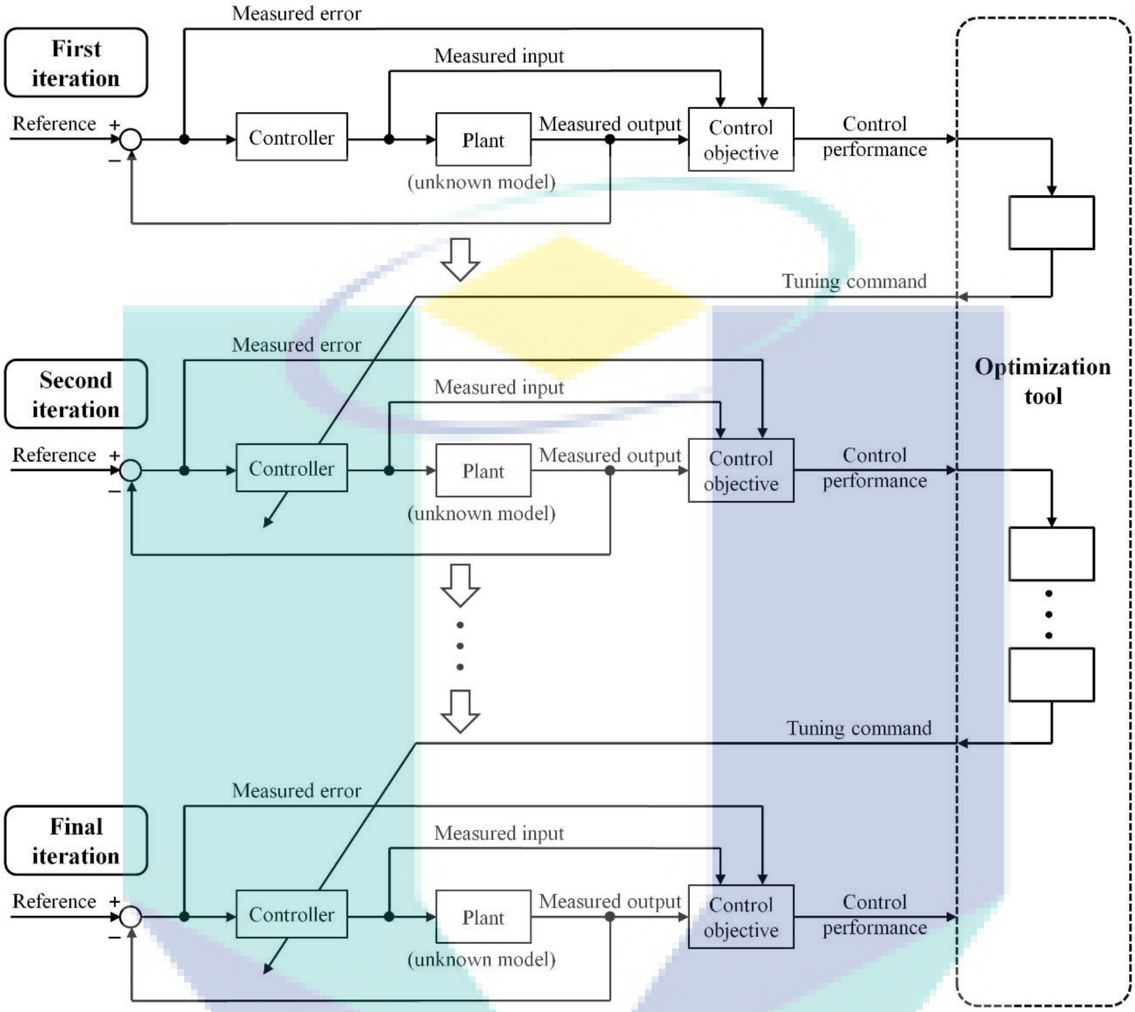

Figure 1.1: Data-driven controller structure

1.1.2 Why data-driven controller design?

The motivation and necessity of data-driven controller design have been discussed in many literatures from the aspects of theory and applications. The main reasons for implementing this approach are summarized as follows:

(i) Independence of the plant models:

Today, with the rapid development of science and technology, practical plants in various fields, such as in the chemical industry, machinery, electronics, electricity, transportation and logistics, have grown up to a large-scale production and the processes have become more complex. As a result, modeling of the plants using first principles or system identification may become more difficult. Even if it is possible to develop such models, it may consume a lot of time and require a significant amount of effort. Therefore, the data-driven control scheme is useful to overcome this situation, since this scheme does not explicitly include any parts or the whole of plant models.

(ii) No gap between control theory and real application:
The data-driven controller design has overcome the unmodeled dynamics problem in the traditional model-based controller design, which may require a robust control framework. In other words, its control performance does not depend on the accuracy of the model. Finally, a huge gap between the control theory and real application vanishes, since the data-driven controller design directly measures I/O data in real time from actual process plants.

(iii) Practical controller design:
From the perspective of practical applications, most of the industrial processes require low-cost and easy-to-install control algorithms. In other words, most of the engineers try to avoid complex mathematics and identification theory (which is the heart of the traditional model-based controller design), since it is hard to understand and requires additional effort and time. Therefore, a data-driven control scheme, which requires less complexity, contributes great practical demands.

From the above reasons, data-driven controller design is useful and it has become one of the important topics to be explored in both theory and applications.

1.1.3 Liquid Slosh Control Problem

Nowadays, slosh or oscillation of liquid inside a container often occurs in many cases. For example, ships with liquid cargo carriers are at high risk of generating sloshing load during operation [1]. In the metal industries, high oscillation can spill molten metal, which is dangerous to handle by the operator [2]. Meanwhile, sloshing of fuel and other liquids in moving vehicles may cause instability and undesired dynamics [3]. Hence, it is necessary to suppress this residual slosh induced by the container motion.

So far, various attempts in suppressing slosh are based on open-loop and closed-loop approaches. For example, input shaping scheme [4], [5] and some filtering techniques [6], [7] are used to generate a prescribed motion, which minimized the residual oscillation. These methods are able to reduce the slosh without needs for feedback sensors. However, these strategies are very poor in handling with any disturbances. On the other hand, closed-loop control or feedback control, which is well known to be less sensitive to disturbances and parameter variations, has also been adopted for reducing slosh. These include PID control [8], H_∞ control [9], sliding mode control [10] and iterative learning control (ILC) [11].

As shown in the above, many approaches use model-based control strategies, which are difficult to apply in practice. This is because their control schemes do not accurately consider the chaotic nature of slosh and the complex fluid dynamic motion in the container. Therefore, a data-driven approach will be more attractive. On the other hand, a Safe Experimentation Dynamics (SED) would provide us a promising tool for data-driven approach. This is because the SED method is known to be effective for a variety of data-driven optimization problems even for high-dimensional parameter tuning [12], [13]. However, it is not clear whether it works for liquid slosh problems, since there are few literatures to discuss the application of the SED to the problems.

1.2 Research Objectives

The objective of this project is given as follows:

(i) To develop a data-driven controller framework based on Safe Experimentation Dynamics (SED) for liquid slosh problem

(ii) To study and analyze the performance of data-driven PID controller tuning based SED in terms of level of slosh suppression, point-to-point tracking capability and speed of the cart response.

1.3 Scope of Project

In order to evaluate the performance of the data-driven approach, an experimental rig is considered, which consists of a small motor-driven liquid tank performing rectilinear motion as shown in Figure 1.2. Moreover, several multi-fluidic sensors are considered to precisely measure the displacement of the liquid surface. Here, the data-driven design is used to tune a given controller (PI, PD or PID) such that the liquid slosh is minimized, while achieving desired cart position. Then, the performance of the proposed method is assessed in terms of level of slosh reduction in time and frequency domains, point-to-point tracking capability, speed of the cart response, and computational complexity. Here, the Matlab and Lab view software were used in the simulation and experimental works.

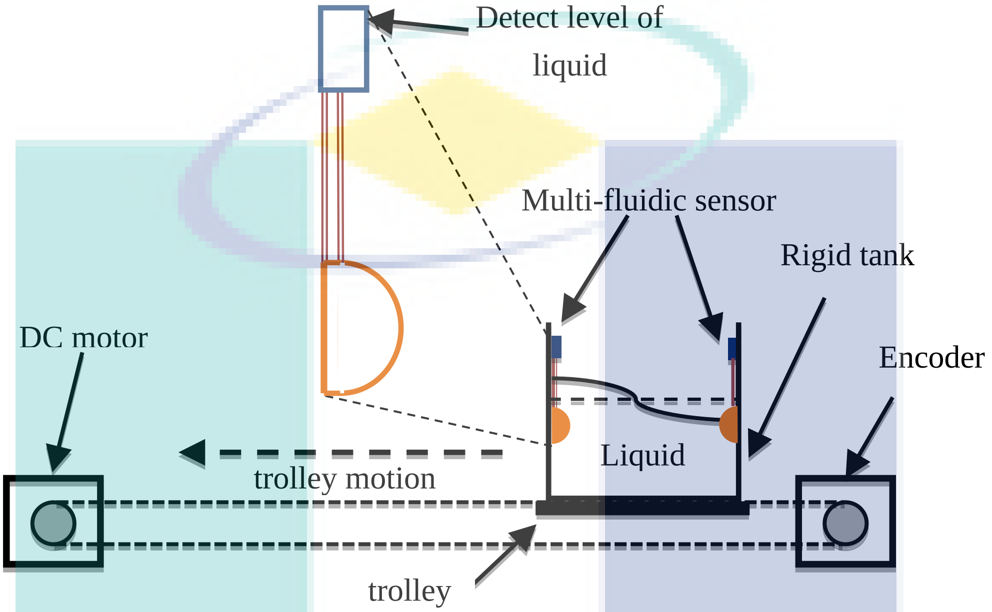

Figure 1.2: Diagram of motor-driven liquid tank system

1.3 Organization of Report

This report is organized as follows.

Chapter 2 describes a literature survey on recent tools in data-driven controller framework. These include the population and trajectory based optimization. Then, we also discussed the existing control schemes for liquid slosh problem, which are monopoly by the model-based control schemes. In addition, we also highlight the motivation of using data-driven control framework based on SED algorithm.

In Chapter 3, a general framework of the data-driven controller design by Safe Experimentation Dynamics algorithm is presented. A step-by-step procedure of the SED algorithm is shown. This is followed by illustrative examples to indicate the effectiveness of the SED algorithm. Then, we show how to implement the standard SED algorithm for a data-driven design controller based on a general control objective function. In the next sub section, the problem formulation of PID control for liquid slosh plant is presented.

This is followed by the procedure of data-driven PID controller design based on SED for liquid slosh problem.

Chapter 4 presents a performance analysis of SED-based algorithm for data-driven PID tuning of liquid slosh systems. Their performances are evaluated in terms of the liquid slosh reduction, tracking performance, and computation time. Furthermore, the performance comparison with other stochastic optimization-based approaches is also considered.

Chapter 5 concludes this report.

Chapter 2

Literature Review

2.1 Review on tools for data-driven controller design

The fundamental essence of the data-driven controller design concerns data-based optimization tools to determine the optimal controller. So far, there exist a large number of data-based optimization methods. In general, they can be divided into two classes of optimization methods:- multi-agent-based optimization and single-agent-based optimization.

The multi-agent-based optimization methods include particle swarm optimization [14], artificial bee colony [15], ant colony optimization [16], bacterial foraging [17], genetic algorithm [18], differential evolution [19], artificial immune system [20], and spiral optimization [21]. These optimization methods, which are also called population-based searches, normally employ a huge number of agents over a large set of feasible solutions. Then, these agents will interact with one another through some specific mechanism and try to improve multiple candidate solutions. However, these methods perform well only for a small number of design parameters, which is no more than 10. In order to handle a large number of design parameters, a cooperative version of them has been introduced, e.g., cooperative co-evolutionary [22], cooperative particle swarm optimization [23], cooperative genetic algorithm [24], and cooperative artificial bee colony [25]. Most of these optimization methods are commonly invented by the computer science community and they have tested their algorithms on artificial benchmark problems, e.g., Rosenbrock, Rastrigin, Griewank, Schaffer and Sphere functions. Therefore, the effectiveness of their optimization methods in the actual control problems is not clear.

Recently, there have also been literatures that use these population-based searches for data-driven controller design such as in tuning the controller for robotic systems [26-29], industrial and automation plant [30-33], renewable energy plant [34-36], and transportation systems [37-39]. However, these optimization tools require heavy computation time to achieve convergence due to the number of evaluated objective functions per iteration being proportional to the number of agents. Thus, a tool that requires less computation time is needed.

Meanwhile, the single-agent-based algorithms, which are also called single solution searches, include random search [40], variable neighborhood search [41], simulated annealing [42], stochastic gradient [43], Tabu search [44,45], simultaneous perturbation stochastic approximation (SPSA) [46], smoothed functional algorithm [47], iterated local search [48], and greedy randomized adaptive search procedure [49]. These approaches concentrate on modifying and improving a single candidate solution based on the random perturbation of its design parameter elements. Therefore, they require less computation time in their design process than the multi-agent-based searches. As a result, these optimization methods would be an attractive tool for the data-driven controller design.

Recent applications of these methods in the data-driven control scheme mostly include the tuning of the parameters in the classical PID controller and intelligent controllers such as fuzzy logics and neural networks. For example, a simulated annealing has been used for the PID tuning in a multi-objective optimization problem. Their method has been evaluated in a super-maneuverable fighter aircraft system [50]. A Tabu search for tuning the PID controller in a simple process plant has been introduced by [51]. Similar work has also been reported in [52] by performing a comparison with Ziegler-Nichols, genetic algorithm and differential evolution methods. In [53,54], a data-driven PID tuning based on the SPSA method has been presented. For example, in [54], the SPSA method has been embedded in a field-programmable gate array (FPGA) for online PID tuning. Meanwhile, for the fuzzy logic controller case, a Tabu search has been used in tuning the fuzzy rules [55] and membership functions [56]. In [57], a simulated annealing is used fortuning the input scaling factor of fuzzy membership functions, and has been tested on a drilling force plant. The similar tuning strategy has been reported in [58] by using the SPSA method for a three-dimensional fuzzy logic controller. On the other hand, in the neural network controller case, the SPSA algorithm is used to tune a large number of neurons of the neural network controller with applications in a water treatment plant [59, 60] and trajectory tracking of a two-link robot [61]. However, most of the presented work only considers a small number of the control design parameters, except for a few results in [59-61]. In addition, there is a possibility that the SPSA algorithm produce an unstable convergence in data-driven control tuning. Therefore, it is necessary to investigate the effectiveness of other single agent based method that utilize the memory feature while produce better control accuracy.

2.2 Motivation of using SED as a tool for data-driven controller design

SED is one of the payoff based learning algorithms in the game theoretic (GT) approach, as presented in [12]. It was called 'safe' because the objective function was evaluated based on the best stored current value, which was non-increasing (in the case of minimization) with respect to the iteration number. SED algorithm performed the optimization by making random perturbation to its design parameters and held the setting if they generated the best value for the objective function [13]. In other words, the SED algorithm making random perturbation only part of its design parameters and hold the best value. Then it will decide whether to maintain or update the design parameters based on the given probability. The key reasons for employing this approach were as follows:

1. Memory-based optimization

The SPSA updated the design parameter tuned based on the gradient approximation which can cause the design parameter to undergo the possibility of change into huge values and unexpectedly caught in an unfeasible area and gave unstable convergence. On the other hand, the significance of the SED based method is the memory stored feature. Whenever the best value of the design parameters is generated for each iteration, the SED method will keep the setting. Due to these characteristics, the SED based method is robust to any disturbance, and uncertain dynamics change during the tuning process. Hence, it is able to produce stable convergence. Although RS is also a memory-based algorithm, it still easily trapped in the local minima problem.

2. Independence of the gain sequence

In the SPSA method, the update law depends largely on the sequence gain that changes per iteration. In consequence, the coefficient value will decrease as the number of iterations increases. Therefore, whenever any disturbance occurs, the performance of SPSA based method degrades as the coefficient value is too small to provide a large step size in the tuning process. On the other hand, the updated law of the SED based method is dependent on the constant value that can be fixed for each iteration. It will then update and store the optimal design parameter. As a result, the presence of disturbance during the tuning process could not affect the performance of the SED based method.

3. Require fewer parameters

In order to give a better performance, the SPSA algorithm is modified where the saturation function is used to avoid the unstable convergence during the tuning process. However, considerable effort is required with the introduction of this saturation function, where we have to determine the additional parameters in advance. Furthermore, the searching capability of the algorithm will be limited by the saturation function. Therefore, the SED based method is seen as an effective approach. It is because a stable convergence can be yielded by the SED algorithm with fewer parameters to be used.

Thus, it would be useful to explore the proposed method capability in tuning the UMS.

In order to test the effectiveness of the SED based method as a data-driven tool for optimization, we focus on the application of SED on the PID controller. Due to its features of simplicity, the fact that it is easily comprehensible and more reliable to the industrial applications, a data-driven PID tuning is seen as one of the most effective data-driven control approaches. Moreover, the data-driven PID controller tunes the design parameters based on the I/O data measurement of the actual plants to achieve a better control performance compared to the model-based PID controller.

Furthermore, some of the reported research regarding the SED algorithm as a tool for the data-driven controller have been applied for the wind farm control system to optimize the total power production, as presented by [12] and [13]. However, the SED algorithm is yet to be used in a data-driven PID controller for the optimization of UMS. Previously, there had been several works that had discussed the application of the SED based method to data-driven PID tuning problems.

2.3 Reviews on Control Schemes for Liquid Slosh Plant

Recently, liquid slosh problems have received a great deal of attention due to their safety issue in vehicle transportations and numerous numbers of applications in various industries. However, controlling such systems still faces numerous challenges that need to be addressed. The control strategies for liquid slosh reduction can be cluster into two main parts, which are mechanical design part and control design part. In mechanical design part, the researchers are interested to improve the whole mechanical structure of tank or vehicle to reduce liquid slosh motion. For example, they may propose different shape of tank or introduce some kinds of damper inside the tank. Meanwhile, in the control design part, they are interested in developing an efficient control algorithm to suppress the slosh. For such a case, they must clearly observe the slosh behaviour through available sensors to detect the slosh. Perhaps, the sensor design for detecting slosh also becomes very interesting topics to be discovered.

Research on improving the mechanical design of tank or carrier has started earlier than the control design part. It is started from 1960 by Budiansky [62], which is the first researcher study on the liquid slosh impact on the circular canal and spherical tanks. Other earlier works are reported in [63] from Fischer, which is then focused on the cylindrical tank. In parallel with software advancement in the past few decades that can simulate the fluid dynamics of slosh with different type of tank shape, many researchers can further improve and optimize the shape of the tank or carrier. Recent works on improving the tank shape are reported in [64-70]. On the other hand, instead of proposing an improved shape of tank, there are also studies on introducing a kind of damper or baffles inside the tank to reduce the liquid slosh. This kind of baffles is promising strategy since it is widely applied for a long type cylindrical tank such as in fuel tank lorry or vessel. Their works reported in [71-79].

The controller design part of liquid slosh motion mostly focused on regulate the cart or trolley (that carrying the liquid) such that it can track a prescribed trajectory precisely with minimum liquid slosh inside the tank. In order to achieve these objectives, various control methods using different techniques have been introduced. Bridgen et al. [4], Aboel-Hassan et al. [5] proposed an input shaping controller, which is in the class of feed-forward control design. This method can be also considered a data-based or data-driven control scheme since it is designed based on the frequency of slosh oscillation data. The relevant work also being done by Baozeng and Lemei [80]. However, the feed-forward control scheme has a drawback of handling any unexpected disturbance since there is no feedback signal to be controlled. Therefore, many researchers are focused on developing numerous feedback control strategies for liquid slosh suppression, such as Sliding Mode Controller [81-86], Linear Quadratic Regulator [87-89], H-infinity [90-91], and Variable Structure Control [92]. Those mentioned methods heavily depend on the state space model of the system, which may not represent the chaotic nature of slosh motion and also may not considering the unmodeled dynamics. A similar class of model-based feedback controller has been reported by Nair et al. [93] and Sira-Ramirez [94]. Here, a nonlinear higher order Sliding Mode Controller and flatness generalized PI control are introduced in [93] and [94], respectively. Meanwhile, in [95], an active force control (AFC) has been proposed by combining it with conventional PID control scheme.

It is shown that the composite PID-AFC provides better slosh reduction than the standalone PID. On the other hand, tools of computational intelligence - such as artificial neural networks and fuzzy logic controllers - have been credited in various applications as powerful tools capable of providing robust controllers for mathematically ill-defined systems. This has led to recent advances in the area of intelligent design in tank shape [96, 97]. Various fuzzy based controllers have been applied in the control of liquid slosh which have led to satisfactory performances [98-101]. Grundelius [11] used an iterative learning control technique for controlling liquid slosh in industrial packaging machine.

Based on the above survey, most of the control designs are highly depend on the developed model. In other words, they need to use the information of the model to design the control parameters. However, the obtained control parameters may not accurately control the real slosh system due to unmodeled dynamics feature in the model and also some simplification to the model. Therefore, it is necessary to develop the control strategy based on the real data from the system instead of using model, which is called data-driven control.

Chapter 3

Data-driven PID based SED for Liquid Slosh Plant

3.1 Safe Experimentation Dynamics

A general framework of the SED algorithm is presented in this section. Consider the optimization problem given by

$$\min_{\boldsymbol{x}\in\mathbb{R}^n} f(\boldsymbol{x}) \tag{3.1}$$

where $f:\mathbb{R}^n \to \mathbb{R}$ is an unknown objective function and $\boldsymbol{x}\in\mathbb{R}^n$ is the design variable.

The SED algorithm iteratively updates the design parameter to search an optimal solution $\boldsymbol{x}^* \in\mathbb{R}^n$ of (3.1). The update law is

$$x_i(k+1) = \begin{cases} \bar{x}_i & , \quad r_1 \geq E\,, \\ h(\bar{x}_i - K_g r_2), & r_1 < E\,, \end{cases} \tag{3.2}$$

where the current best value of the design parameters is stored as $\bar{\boldsymbol{x}}$. The symbol x_i is the i-th element of $\boldsymbol{x}$ and $\bar{x}_i$ is the i-th element of $\bar{\boldsymbol{x}}\in\mathbb{R}^n$, with $k=0,1,\cdots,$ is the number of iteration. Note that, E is a scalar that defines the probability to use a new random setting for $\boldsymbol{x}$ and the interval size to decide on the random step on $\boldsymbol{x}$ is defines by a scalar K_g. Meanwhile r_1 is a random value that is uniformly distributed between 0 and 1 and the random value r_2 is between $x_{\min}$ and $x_{\max}$. The function h in (3.2) is given as shown in (3.3).

$$h(\cdot)=\begin{cases} x_{\max} \quad , & \bar{x}_i - K_g r_2 > x_{\max} \quad , \\ \bar{x}_i - K_g r_2 , & x_{\min} \le \bar{x}_i - K_g r_2 \le x_{\max} \quad , \\ x_{\min} \quad , & \bar{x}_i - K_g r_2 < x_{\min} \quad , \end{cases} \tag{3.3}$$

In (3.3), $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the design parameters that are pre-defined respectively. Then, the course of action of SED algorithm is described as follows:

Step 1: Determine the value for $x_{\min}$, $x_{\max}$, K_g and E. Then, set $k = 0$ and the initial condition for the design parameter is set as $\boldsymbol{x}(0)$ and the objective function be $f(\boldsymbol{x}(0))$. As a default, the current best value of the design parameter and objective function are set as $\bar{\boldsymbol{x}} = \boldsymbol{x}(0)$ and $\bar{f} = f(\boldsymbol{x}(0))$ respectively.

Step 2: If the value of the objective function at the kth iteration, $f(\boldsymbol{x}(k)) < \bar{f}$, the obtained design parameter is store as $\bar{\boldsymbol{x}} = \boldsymbol{x}(k)$ and the objective function is store as $\bar{f} = f(\boldsymbol{x}(k))$. Otherwise, proceed to step 3.

Step 3: Generate a random number r_1. If $r_1 < E$, generates a second random number r_2 and obtains the value for $x_i(k+1)$ using the updated law in (3.2). Otherwise, $x_i(k+1) = \bar{x}_i$

Step 4: Obtain the objective function $f(\boldsymbol{x}(k+1))$.

Step 5: After the pre-stated termination condition is fulfilled, the algorithm terminates with the solution $\boldsymbol{x}^* := \arg \min_{x\in\{x(0),x(1),\dots,x(k+1)\}} f(\boldsymbol{x})$. Otherwise, for the next iteration, set $k = k+1$ and continue to step 2.

The pre-stated termination condition is based on the chosen maximum number of iterations $k_{\max}$.

3.2 Convergence conditions of the SED algorithm

This section presents the convergence conditions of the standard SED algorithm, which can be described in the following theorem.

Theorem 3.1. [12] Let G be a finite n-player identical interest game in which all players use the SED. Given any probability $E<1$, if the searching rate $K_g>0$ is adequately small, then for all adequately large times t, $x(t)$ is an optimal Nash equilibrium of G with at least probability E.

Proof. Let the utility of each player be stated as $f:\mathrm{A}\rightarrow\mathbb{R}$, since G is an identical interest game and let A^* be the set of "optimal" Nash equilibrium of G as in (3.4).

$$\mathrm{A}^*=\left\{x^*\in\mathrm{A}:f(x^*)=\max_{x\in\mathrm{A}} f(x)\right\}. \tag{3.4}$$

For any joint, $x(t)$, the ensuing joint action will be found an optimal Nash equilibrium with at least probability

$$\left(\frac{K_g}{|\mathrm{A}_1|}\right)\left(\frac{K_g}{|\mathrm{A}_2|}\right)\cdots\left(\frac{K_g}{|\mathrm{A}_n|}\right), \tag{3.5}$$

where $|\mathrm{A}_i|$ represents the cardinality of the action set of players P_i. In the end, an optimal Nash equilibrium will be played with probability 1 for any $K_g>0$.

Assume at the time t^* an optimal Nash equilibrium is first played, for example, $x(t^*)\in\mathrm{A}^*$ and $x(t^*-1)\notin\mathrm{A}^*$. Then the baseline joint action must remain constant from that time onwards. An optimal Nash equilibrium will then be played at any time $t>t^*$ with at least probability $(1-K_g)^n$. Since $K_g>0$ can be chosen arbitrarily small and such that $(1-K_g)^n>E$, this completes the proof.

3.3 Illustrative Examples

In this section, we present two examples to illustrate the effectiveness of the standard SPSA algorithm in the previous section.

Example 1: Consider a smooth Rastrigin test function with n = 10 given by

$$f(\boldsymbol{x}) = \sum_{i=0}^{n}\left(x_i^2 - 10\cos(2\pi x_i) + 10\right), \tag{3.6}$$

where $n = 10$, $\boldsymbol{x} = [x_1, x_2, \cdots, x_n]^T$. Note that $f(\boldsymbol{x}^*) = 0$ at $\boldsymbol{x}^* = [0, 0, \ldots, 0]^T$. After performing several preliminary simulations, the initial condition is selected to be close to $\boldsymbol{x}^*$. Let $\boldsymbol{x}(0) = [0.05, 0.05, \ldots, 0.05]^T$ that yield $f(\boldsymbol{x}(0)) = 4.9193$. Then, we set $x_{\max} = 2.0$, $x_{\min} = -2.0$, $E = 0.8$ and $K_g = 0.001$. While for NL-SPSA, we set $a = 0.8$, $A = 12$, $\alpha = 1$, $\gamma = 1/6$ and $d = 0.02$.

Figure 3.1 shows the performance for the convergence curve of objective function between SED and NL-SPSA for 1000 iterations. Based on the graph, SED provided better objective function accuracy than NL-SPSA. Even though NL-SPSA uses two times objective function evaluations in one iteration compared to SED.

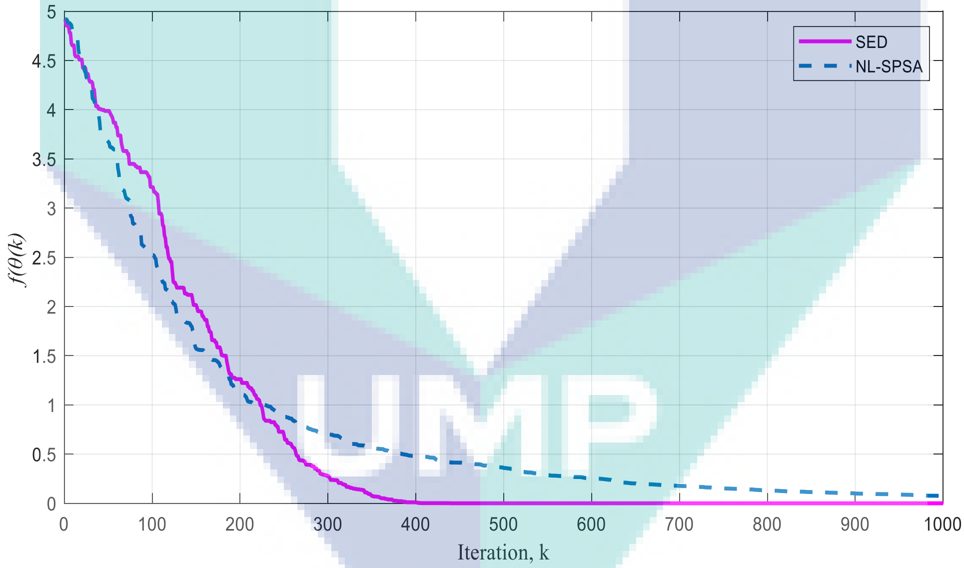

Figure 3.1: Response of the objective function $f(\boldsymbol{x}(k))$ in Example 1

Example 2: Consider a non-smooth Ackley test function given by

$$f(\boldsymbol{x}) = \left(\frac{1}{0.8}\right)\left(-20e^{-0.2\left(\frac{1}{n}\sum_{i=1}^{n} x_i^2\right)^{0.5}} - e^{\frac{1}{3}\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi|x_i|)\right)}\right), \tag{3.7}$$

where $n=3$, $\boldsymbol{x}=[x_1,\ x_2,\ \ldots,\ x_n]^T$ and $f(\boldsymbol{x}^*)=0$ at $\boldsymbol{x}^*=[0,0,\ldots,0]^T$. Let $\boldsymbol{x}(0)=[1,1,\ldots,1]^T$, that yields $f(\boldsymbol{x}(0))=4.5317$. Then, we set $x_{\max}=2.0$, $x_{\min}=-2.0$, $E=0.8$ and $K_g=1$. While for the NL-SPSA, we set $a=0.002$, $A=150$, $\alpha=0.9$, $\gamma=1/6$, $\delta=0.1$ and $d=0.5$.

Figure 3.2 shows the performance for the convergence curve of objective function between SED and NL-SPSA for 1000 iterations. In this graph, although SED is slower in the curve convergence, the SED can reach an optimal solution which is better than NL-SPSA.

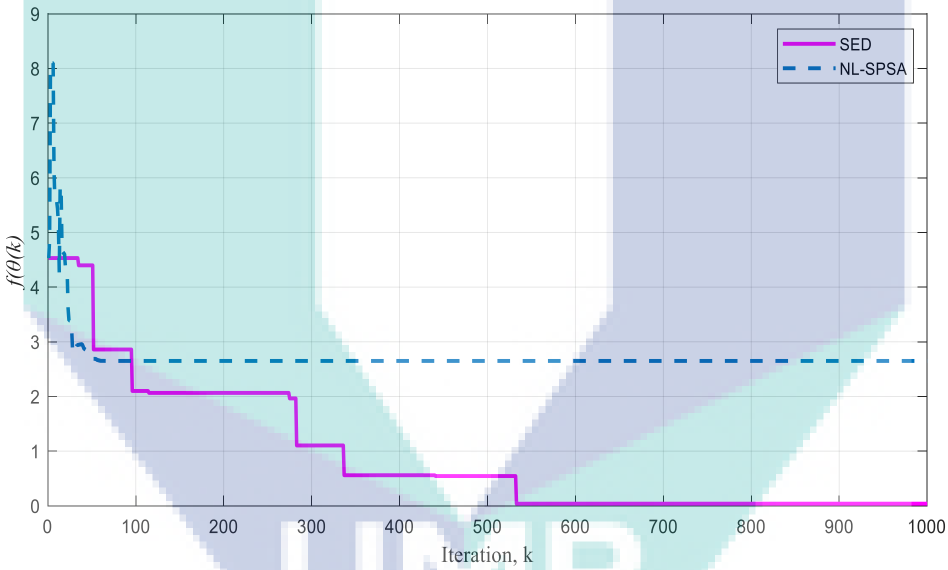

Figure 3.2: Response of the objective function $f(\boldsymbol{x}(k))$ in Example 2

Both examples clarify that the SED algorithm can solve high-dimensional problems by using only one measured objective functions per iteration. Also, the SED algorithm is applicable to both smooth and non-smooth objective functions as long as the measured objective functions are available. Therefore, these facts indicate that this algorithm is a promising tool for a data-driven control scheme.

3.4 Framework of Data-driven Controller Design based on SED

Firstly, it is presented on how to apply the SED algorithm to the data-driven controller design. In general, let $J(\boldsymbol{\kappa}):\mathbb{R}^n \to \mathbb{R}$ be the function specifying the controller performance and $\boldsymbol{\kappa} \in \mathbb{R}^n$ be the control parameter. Assume that the relation between $\boldsymbol{\kappa}$ and J is unknown. Then, a general data-driven controller design is summarized as follows:

Step 1: Determine the initial value $\boldsymbol{\kappa}(0)$ and a pre-specified termination criterion.

Step 2: Perform the SED algorithm in Chapter 3.1 to the objective function J and the design parameter $\boldsymbol{\kappa} := (\kappa_1, \kappa_2, \ldots, \kappa_n)$, i.e., by regarding J and $\boldsymbol{\kappa}$ as f and $\boldsymbol{\theta}$, respectively.

Step 3: After the pre-specified termination criterion is satisfied, the algorithm terminates with the solution $\boldsymbol{\kappa}^* = \boldsymbol{\theta}^*$.

Next, it is worth to clarify the applicable condition of this framework. Basically, the above framework can be applied to a given closed-loop feedback system, which already consists of a stabilizing controller for an unknown plant model. Here, the data-driven controller design scheme is used to improve the control performance of the given system by tuning its stabilizing controller based only on the I/O data of the plant.

3.5 Problem Formulation of PID Control for Liquid Slosh Plant

Consider the PID control system for liquid slosh problem depicted in Figure 3.3, where the reference, control input, the lateral axis of the tank measurement and the slosh angle measurement is respectively represented by $r(t)$, $u(t)$, $y(t)$ and $\theta(t)$. While plant G, represented the liquid slosh system.

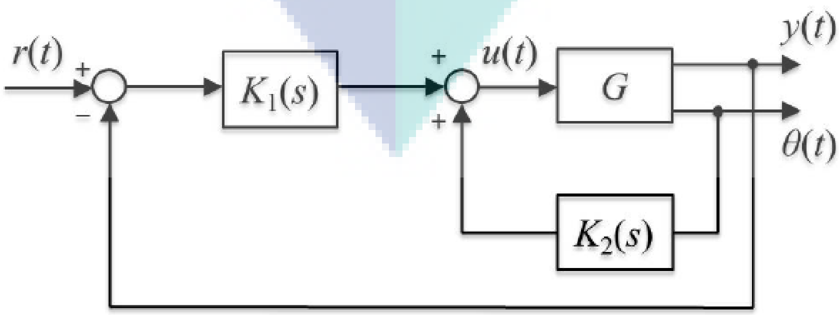

Figure 3.3: Liquid Slosh PID Control System

The symbol $K_i(s)$ $i = 1,2$ is the controller that given for the PID controller

$$K_i(s) = P_i\left(1 + \frac{1}{I_i s} + \frac{D_i s}{1 + (D_i / N_i)s}\right) \tag{3.8}$$

where $P_i \in \mathrm{R}$, $I_i \in \mathrm{R}$, $D_i \in \mathrm{R}$ and $N_i \in \mathrm{R}$ is the proportional gain, integral time, derivative time and filter coefficient respectively. Next, in Fig. 3.3, the performance index of the control system is introduced. Let

$$\hat{e} = \int_{t_0}^{t_f} |r(t) - y(t)|^2 \, dt, \tag{3.9}$$

$$\hat{\theta} = \int_{t_0}^{t_f} |\theta(t)|^2 \, dt, \tag{3.10}$$

$$\hat{u} = \int_{t_0}^{t_f} |u(t)|^2 \, dt, \tag{3.11}$$

where the time interval $[t_0, t_f]$ correspond to the period of the performance evaluation, $t_0 \in \{0\} \cup \mathrm{R}_+$ and $t_f \in \mathrm{R}_+$. The objective function is interpreted as follows

$$J(\mathbf{P}, \mathbf{I}, \mathbf{D}, \mathbf{N}) = w_1 \hat{e} + w_2 \hat{\theta} + w_3 \hat{u}, \tag{3.12}$$

where $\mathbf{P} = [P_1 \quad P_2]^{\mathrm{T}}$, $\mathbf{I} = [I_1 \quad I_2]^{\mathrm{T}}$, $\mathbf{D} = [D_1 \quad D_2]^{\mathrm{T}}$ and $\mathbf{N} = [N_1 \quad N_2]^{\mathrm{T}}$. $w_1 \in \mathrm{R}$, $w_2 \in \mathrm{R}$ and $w_3 \in \mathrm{R}$ are the designated weighting coefficients by the designer and the values are chosen with the same method of the standard Linear Quadratic Regulator (LQR) problem. The expressions $w_1\hat{e}$ and $w_2\hat{\theta}$ in (3.12) corresponded to the tracking error, while $w_3\hat{u}$ expression corresponded to the control input energy. Thus, the optimization problem for data-driven PID controller can be expressed as follows:

Problem 3.1. Find the $K(s)$, a PID controller where the control objective $J(\mathbf{P}, \mathbf{I}, \mathbf{D}, \mathbf{N})$ with respect to **P, I, D**, and **N** is minimizes in corresponded with the measurement data $(u(t), y(t), \theta(t))$, for the PID control system in Figure 3.3.

3.6 Data-driven PID Controller Design Based on SED

In this section, the SED algorithm in Section 3.1 is applied for data-driven PID tuning. Firstly, let the design parameter is defined as follows:

$$\psi = [\mathrm{P}_1\ \mathrm{P}_2\ \mathrm{I}_1\ \mathrm{I}_2\ \mathrm{D}_1\ \mathrm{D}_2\ \mathrm{N}_1\ \mathrm{N}_2]^{\mathrm{T}} \in \mathrm{R}^8 \tag{3.13}$$

The logarithmic scale is employed to the design parameter ψ to accelerate the exploration of the design parameter with the setting of $\psi_i = 10^{\theta_i}\ (i = 1,2,\ldots,8)$, and the objective function can be expressed as $J = [10^{\theta_1}\quad 10^{\theta_2}\quad \cdots\quad 10^{\theta_8}]^{\mathrm{T}}$. Finally, our design procedure is described as follows:

Step 1: Let $\theta_i = \log \psi_i$ and determine the maximum iteration number, $k_{\max}$.

Step 2: Perform SED algorithm in Section 3.1 for the objective function in (3.12).

Step 3: After reaching $k_{\max}$, record the optimal output $\boldsymbol{\theta^*} = \boldsymbol{\theta}(\boldsymbol{k_{max}})$. Then, apply the $\psi^* = [10^{\theta_1^*}\quad 10^{\theta_2^*}\quad \cdots\quad 10^{\theta_8^*}]^{\mathrm{T}}$ to $K_i(s)$ in the PID control system in Figure 3.3.

Chapter 4

Results and Discussions

In this chapter, the effectiveness of the proposed data-driven PID tuning based on SEDis demonstrated. Firstly, a liquid slosh model is briefly described. Then, the SED based method is tested to the developed model.

4.1 Liquid Slosh Plant and Model

In order to develop the liquid slosh model, we consider a real plant of liquid slosh plant as shown in Figure 4.1. This plant or experimental setup is important to evaluate the effectiveness of the proposed data-driven controller approach. The detail description of the plant is given as follows:

(i) **Mechanical structure**
It involves the development of platform for rectilinear motion of the trolley. The travelling range of the trolley which carries the liquid tank is around 100 mm. A cube water tank with dimension 150 x 150 x150 mm is considered.

(ii) **System actuator and position measurement**
The liquid slosh plant has only one actuator to drive the rectilinear motion of the trolley. Here, we will use a single DC motor with embedded high resolution encoder to precisely observe the position of the trolley. Note that the rotation of the DC motor will move the trolley in a rectilinear motion either forward or backward movement.

(iii) **Data acquisition mechanism**
In this study, the proposed control scheme is developed in Matlab/Lab view software and it will control the liquid slosh plant in real time. On the other hand, we also can develop our own liquid slosh model from input and output data of liquid slosh plant. Therefore, we need a data acquisition card to communicate the liquid slosh plant with the control environment in PC. In particular, we can send

the signal from the PC (through Matlab/Lab view software) to rotate the DC motor while recording the position of the trolley from the plant to the PC, simultaneously.

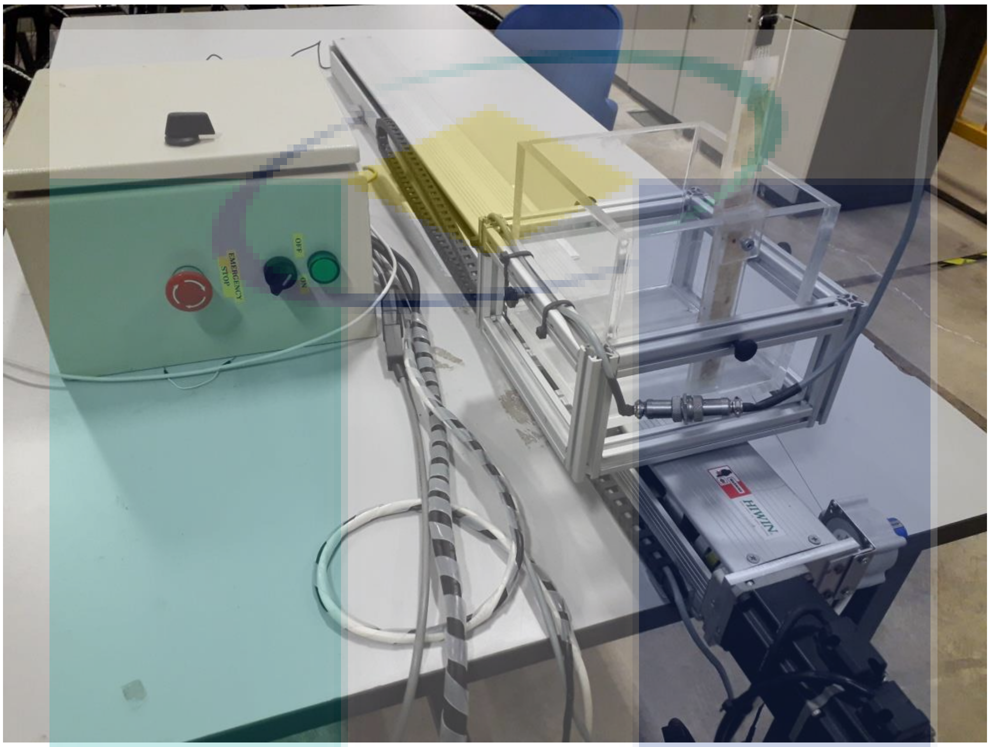

Figure 4.1: Experimental rig of liquid slosh plant

Our liquid slosh model is developed using the combination of system identification and first principle methods. In particular, we adopt the standard model of liquid slosh plant from [10], as shown below:

$$M\ddot{y} + ml\cos\theta\ddot{\theta} - ml\dot{\theta}^2\sin\theta = u, \tag{4.1}$$

$$ml\cos\theta\ddot{y} + ml^2\ddot{\theta} + d\dot{\theta} - mgl\sin\theta = 0, \tag{4.2}$$

where M , m , l , d and g are respectively the mass of the tank with liquid, mass of the liquid, liquid slosh hypotenuse length, damping coefficient and gravity. Note that the above model or system's dynamic equation is developed using the Euler-Lagrange formulation. Then, the parameters of M , m , l , d and g in (4.1) and (4.2) are determined using the system identification method, where the input and output data are taken from our real liquid slosh plant by applying a quick-stop experiment. The real parameters of the plant are depicted in Table 4.1, after using the system identification tool box in Matlab.

Table 4.1: Parameters of Liquid Slosh Model

Parameter	Value	Unit
M	6.0	kg
m	1.32	kg
l	0.052126	m
d	3.0490×10-4	kg m^2/s
g	9.81	m/s^2

4.2 Performance Comparison and Analysis

Based on the obtained liquid model in Section 4.1, we apply the proposed data-driven PID based SED using the Matlab environment. In order to evaluate the performance of the SED-based methods, we perform 30 independent trials to the liquid slosh model. Then, after the termination criterion is satisfied, the proposed method is evaluated based on the following performance criteria

(i) The statistical analysis of the objective function $J(\boldsymbol{P},\boldsymbol{I},\boldsymbol{D},\boldsymbol{N})$, total norm of the error $\hat{e}$, slosh angle $\hat{\theta}$ and total norm of the input $\hat{u}$. Specifically, the mean, best, worst, and standard deviation values of them are observed from 30 independent trials.

(ii) Time Response Analysis, which are the rise time, settling time, and percentage of overshoot of the one best trial out of the 30 trials are observed.

(iii) Computation time after 30 trials and percentage of control objective improvement $Q\% = ((Q_{\text{initial}} - Q_{\text{final}}) / Q_{\text{initial}}) \times 100$, The symbol $Q_{initial}$ is the $J(\boldsymbol{P},\boldsymbol{I},\boldsymbol{D},\boldsymbol{N})$ average value of the first iteration. The symbol Q_{final} is the $J(\boldsymbol{P},\boldsymbol{I},\boldsymbol{D},\boldsymbol{N})$ average value of the final iteration.

Note that we use the same performance indexes to evaluate the performance of the G-NL-SPSA, NL-SPSA, and RS based methods.

The controller $K_i(s)$ $i=1,2$ is the PID controller in a feedback control structure as shown in Figure 3.3. Next, the reference cart/trolley position as follow:

$$\boldsymbol{r}(t)=\begin{cases}0, & 0\le t\le 1 \quad ,\\ 0.5, & 1<t\le 20\,.\end{cases} \tag{4.3}$$

The value of weighting coefficients $w_1=100$, $w_2=50$, $w_3=5$, the time interval $t_0=0$, $t_f=20$ are set for SED, NL-SPSA, G-NL-SPSA, and RS based methods. Next, the values of the pre-defined parameters for all the algorithms are set as depicted in Table 4.2. As the SPSA based algorithm evaluates the objective function twice in one iteration, the $k_{\max}$ .value is set half from the $k_{\max}$ value for SED and RS algorithms.

Table 4.2: Pre-designed Parameters of All Algorithms for Slosh Control System

Algorithm	Pre-defined Parameter	Value
SED	$x_{\max}$	3.5000
	$x_{\min}$	−2.0000
	E	0.6600
	K_g	0.0220
	$k_{\max}$	200
NL-SPSA	a	0.0050
	A	23
	α	0.6000
	c	0.2000
	γ	0.1000
	δ	0.1000
	$k_{\max}$	100
G-NL-SPSA	a	0.0300
	A	20
	α	0.6000
	c	0.0500
	γ	0.1000
	δ	0.0500
	B	80000
	b	0.1300
	$k_{\max}$	100

Table 4.2: Continued

Algorithm	Pre-defined Parameter	Value
RS	$x_{\max}$	3.5000
	$x_{\min}$	−2.0000
	r_1	0.0800
	$k_{\max}$	200

Table 4.3 show the initial condition for $\boldsymbol{x}(0)$ and the optimal design parameters $\boldsymbol{x}^*$ for the SED based method, while for the NL-SPSA, G-NL-SPSA and RS based methods can be referred to in Table 1 of Appendix A. These values are tabulated from the best response out of the 30 trials. Note that, the value of ψ corresponds to $\boldsymbol{x}(0)\times 10^3$ and $\boldsymbol{\psi}^*$ corresponds to $\boldsymbol{x}^* \times 10^3$.

Table 4.3: Design Parameters of SED for Liquid Slosh

$\boldsymbol{\psi}$	**PID Gain**	$\boldsymbol{x}(0)$	ψ	$\boldsymbol{x}^*$	$\boldsymbol{\psi}^*$
ψ_1	P_1	1.0000	0.0100	0.0884	0.0012
ψ_2	P_2	3.5000	3.1622	2.7355	0.5439
ψ_3	I_1	0.0000	0.0010	0.4033	0.0025
ψ_4	I_2	1.0000	0.0100	0.4450	0.0029
ψ_5	D_1	2.0000	0.1000	0.8124	0.0065
ψ_6	D_2	1.0000	0.0100	−0.5094	0.0003
ψ_7	N_1	0.0000	0.0010	−0.9655	0.0001
ψ_8	N_2	1.0000	0.0100	0.5023	0.0032

Table 4.4 depicts the control performances in terms of the objective function, norm of error and norm of input. After 30 trials, the statistical results are obtained for each of the algorithms.

Table 4.4: Statistical Results for Liquid Slosh Control System

Algorithm		**RS**	**NL-SPSA**	**G-NL-SPSA**	**SED**
$J(\boldsymbol{P},\boldsymbol{I},\boldsymbol{D},\boldsymbol{N})$	Mean	42.2710	42.4064	41.9701	**41.6050**
	Best	**41.2801**	41.6587	41.2987	41.3302
	Worst	43.1873	43.7629	44.3735	**42.5669**
	Std	0.4597	0.5079	0.6045	**0.1975**
Total Norm of Error $(\hat{e}+\hat{\theta})$	Mean	0.3185	0.3219	0.3225	**0.3169**
	Best	0.3030	03102	**0.2887**	0.3060
	Worst	**0.3402**	0.3515	0.3533	0.3521
	Std	0.0085	0.0086	0.0129	**0.0063**
Total Norm of Input $(\hat{u})$	Mean	2.1703	2.0924	**1.9709**	2.0040
	Best	1.8853	1.8211	**1.5686**	1.8067
	Worst	2.8136	2.4319	2.6442	**2.4167**
	Std	0.2285	0.1473	0.2179	**0.1092**
Computation Time (s)		37.6361	50.0853	54.9654	**35.1637**
Average Percentage of Control Objective Improvement, $Q\%$		94.9368	94.9207	94.9726	**95.0160**

Based on the results shown in Table 4.4, it is proven that the SED based method produces better mean values for the objective function and the total norm of error. It is also shown that the SED based method produces lower standard deviation values for the objective function, total norm of error, and total norm of input. Moreover, the computation time achieved by SED based method is faster than the other methods. Then, the average percentage of control objective improvement, $Q\%$ for all methods are also shown in Table 4.4. Based on the percentage results, the objective improvement for SED based method is marginally better than the RS, NL-SPSA and G-NL SPSA based methods.

The objective function response for SED, NL-GSPSA, NL-SPSA, and RS based methods is shown in Figures 4.2, 4.3, 4.4, and 4.5, respectively. The SED and RS algorithms use twice the iteration number from NL-GSPSA and NL-SPSA algorithms because SPSA based algorithms use two objective functions to update the controller parameters. These responses are taken from the best plot out of the 30 trials. Based on the results, the SED based method is proven capable of minimizing the objective function.

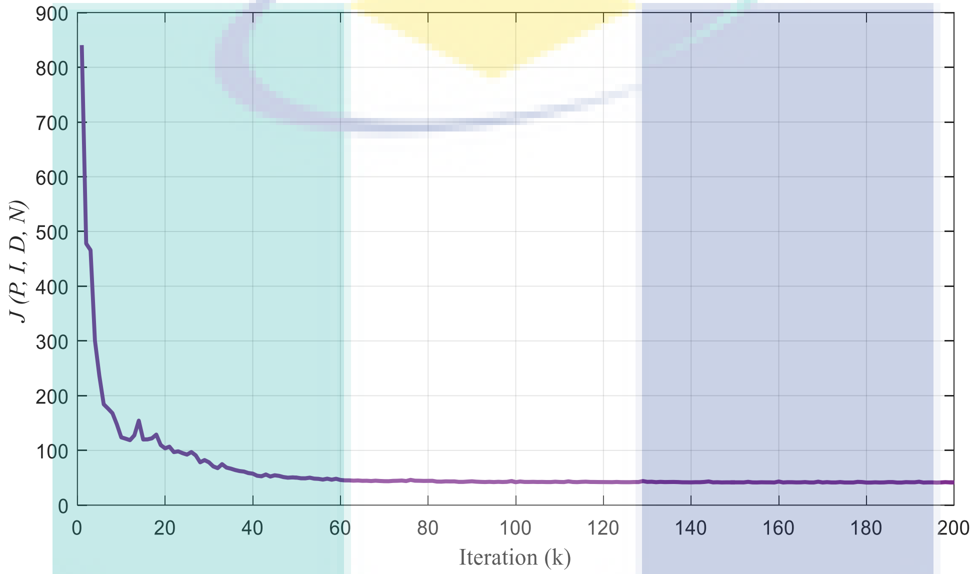

Figure 4.2: SED Objective Function Response for Liquid Slosh Control System

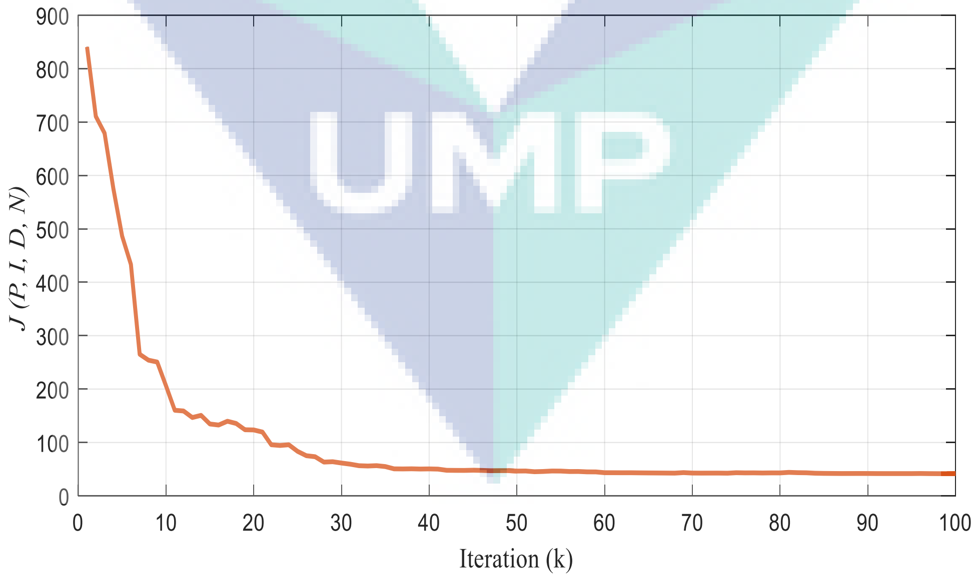

Figure 4.3: NL-GSPSA Objective Function Response for Liquid Slosh Control System

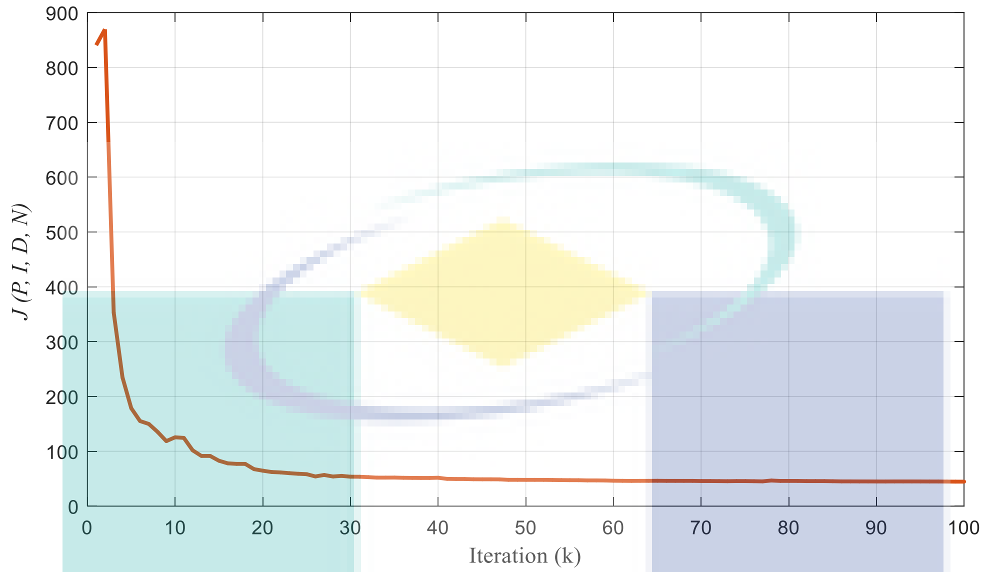

Figure 4.4: NL-SPSA Objective Function Response for Liquid Slosh Control System

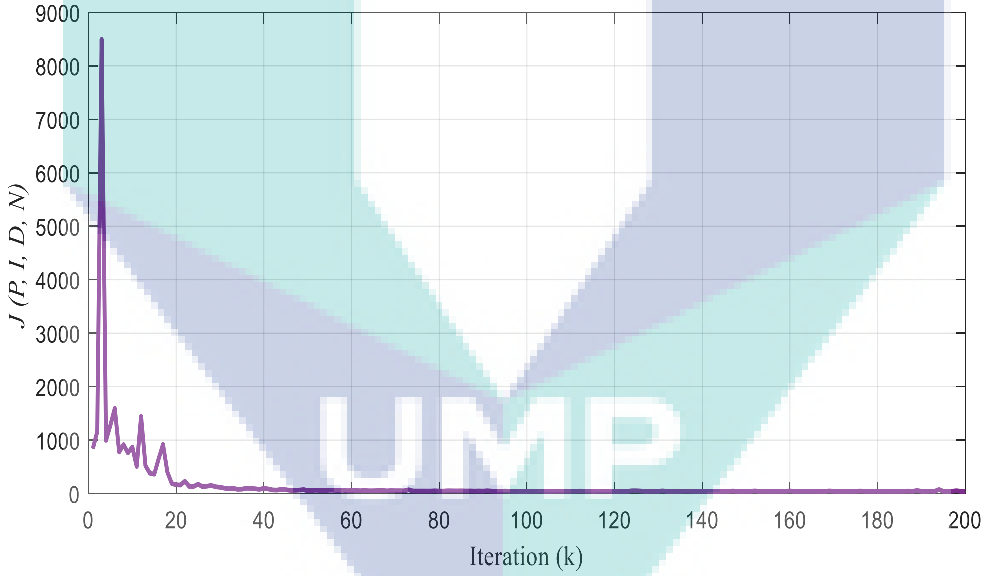

Figure 4.5: RS Objective Function Response for Liquid Slosh Control System

Next, the responses for the cart position are shown in Figure 4.6 for all the four methods. In this graph, the black dash line indicates the reference signal for the cart position, the initial response of the cart position is indicated by the grey color line, whereas the black line and green dash-dotted line indicate the responses after 200 iterations for SED and RS, respectively. The red dash line and blue dotted line, on the other hand, indicate the response after 100 iterations for the G-NL-SPSA and NL-SPSA methods respectively.

The results displayed in Figure 4.6 illustrate that the SED based method efficiently attains the desired trolley position compared to the other methods Figure 4.7, on the other hand, displays the result in terms of the slosh angle response. It is shown that the SED based method has successfully reduced the slosh magnitude, although a slight oscillation occurs, and it is comparable with the result of the other methods. This is supported by the faster settling time by SED based method in minimizing the slosh angle magnitude which is 6.4010s compared to the G-NL-SPSA, NL-SPSA and RS based methods' settling times are 7.0555s, 7.6104s, and 7.3211s respectively. Nevertheless, Figure 4.8 shows that the SED based method uses smaller control input energy compared to the initial response.

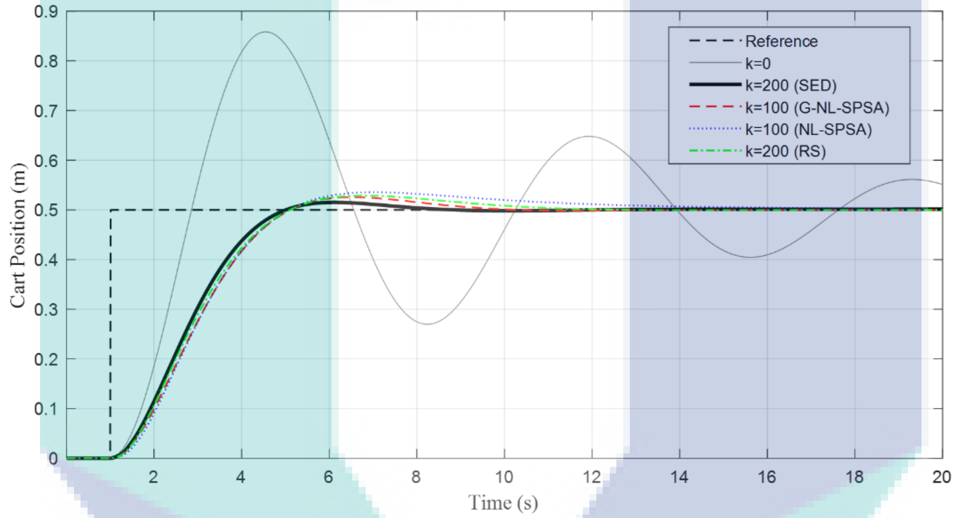

Figure 4.6: Cart Position Response for Liquid Slosh Control System

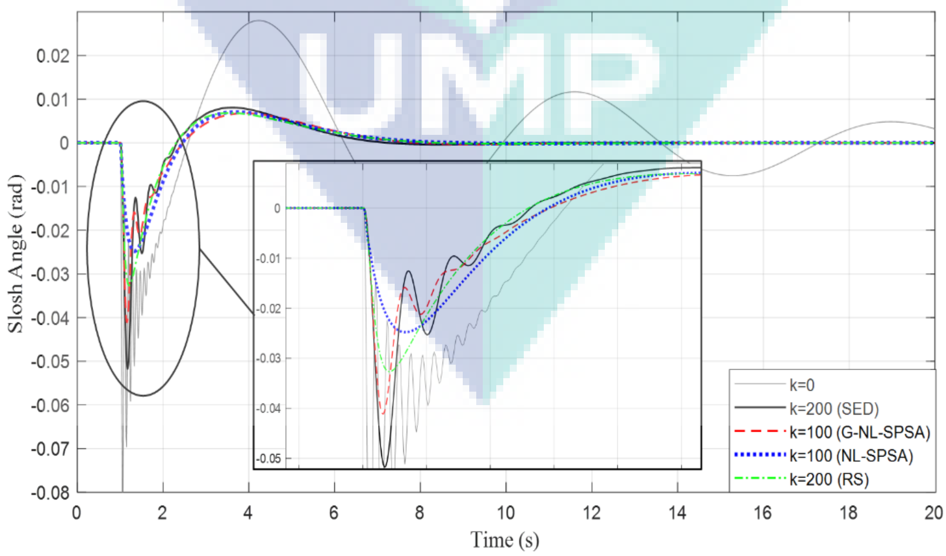

Figure 4.7: Slosh Angle Response for Liquid Slosh Control System

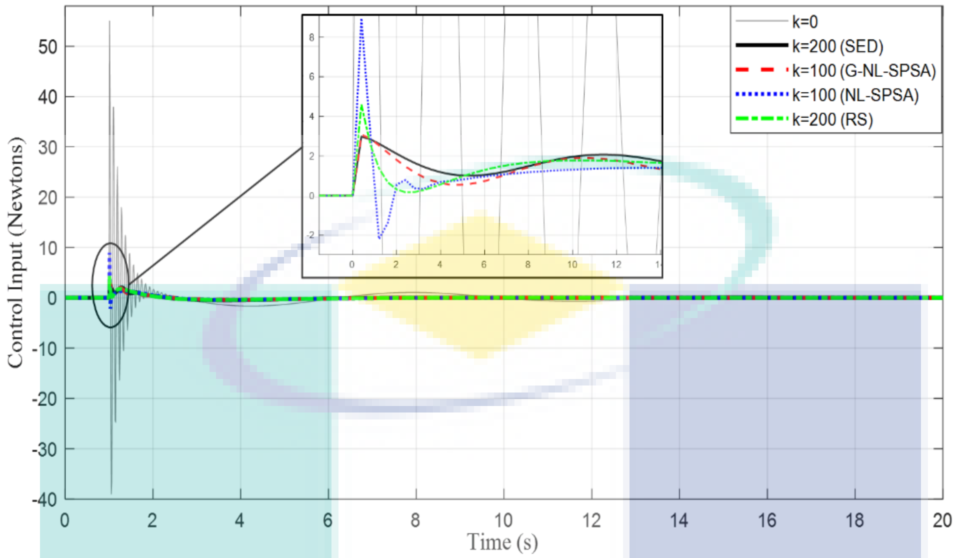

Figure 4.8: Control Input Response for Liquid Slosh Control System

Next, Table 4.5 shows the time response specification of the trolley position for all the methods.

Table 4.5: Time Response Specification for Slosh Control System

Algorithm	Trolley Position Rise Time (s)	Trolley Position Settling Time (s)	Trolley Position Overshoot (%)	Control Input Settling Time (s)
SED	**2.5319**	**6.9521**	**2.7589**	6.4164
G-NL-SPSA	2.6637	8.5454	5.0710	6.8961
NL-SPSA	2.6089	11.7745	6.6875	**5.7133**
RS	2.6310	9.7065	5.7517	6.5141

Based on the results, the settling time taken for SED based method is less compared to the other methods for the trolley to attain the desired position with slightly faster rise time and smaller percentage of overshoot compared to G-NL-SPSA, NL-SPSA, and RS based methods. Even though the NL-SPSA obtains the faster settling time of control input response, SED based method still produces comparable settling time with G-NL-SPSA, NL-SPSA, and RS based methods.

Chapter 5

Conclusion

In this research report, a framework of data-driven control scheme based on the simultaneous perturbation stochastic approximation has been established. Based on the general step-by-step procedure of this framework in Chapter 3, the effectiveness of the SED-based method has been investigated for liquid slosh control problem. The goal is to obtain the optimal PID control parameter based on only input and output data such that the liquid slosh is minimized while the cart position follows the desired trajectory. In general, it shows that the SED-based methods have a good potential in obtaining acceptable results within a few minutes through extensive simulation and experimental works. In particular, from the control performance and the statistical results indicate that the SED-based algorithm outperforms other stochastic optimization-based methods.

As shown in the above, the main philosophy of the proposed framework is that it can be applied to improve the given stabilizing controller of systems with unknown plant models such that the control performance is achieved. Our investigation shows that the data-driven controller scheme based on SED has a good potential in improving the given stabilizing controller by using only the I/O data of the plant. In particular, based on the above control problems, this framework has successfully accomplished the desired control objective by tuning a large number of control parameters in a practical convergence time. Moreover, we have shown that some modifications to the standard SED algorithm are necessary to handle each control problem. Note that these modifications are unique for each problem and it would become an informative guideline for others in solving a similar problem framework.

Finally, this report is concluded by highlighting some open problems as follows: The first is to develop theoretical results for data-driven controller design framework. In particular, a new stability analysis for data-driven controller design, which is based on only I/O measurement data, would be an important topic to be explored. The second is the robustness issues in data-driven controller design. Here, a new definition of robustness of data-driven controller framework should be considered, unlike the model-based controller, where the robustness refers to the ability of controllers to deal with unmodeled dynamics. The third is to upgrade the optimization tool such that it converges to a global solution with fast controller tuning. This appealing feature implies that the algorithm may automatically combine the broad search required for global optimization with the localized search that is tied to the gradient approximation.

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Appendix A: Design Parameter for NL-SPSA, G-NL-SPSA and RS

Table 1 Design Parameters of Slosh Control System

Initial Design Parameters				**Optimal Design Parameters for NL-SPSA**		**Optimal Design Parameters for G-NL-SPSA**		**Optimal Design Parameters for RS**	
ψ	**PID Gain**	$\boldsymbol{x}(0)$	ψ **corresponded to** $\boldsymbol{x}(0)\times 10^3$	$\boldsymbol{x}^*$	ψ^* **corresponded to** $\boldsymbol{x}^*\times 10^3$	$\boldsymbol{x}^*$	ψ^* **corresponded to** $\boldsymbol{x}^*\times 10^3$	$\boldsymbol{x}^*$	ψ^* **corresponded to** $\boldsymbol{x}^*\times 10^3$
ψ_1	P_1	1.0000	0.0100	0.4349	0.0027	0.2621	0.0018	−0.3190	0.0005
ψ_2	P_2	3.5000	3.1622	3.5765	3.7714	3.6138	4.1096	3.3274	2.1252
ψ_3	I_1	0.0000	0.0010	0.1164	0.0013	0.1557	0.0014	0.8671	0.0074
ψ_4	I_2	1.0000	0.0100	0.4656	0.0029	0.2376	0.0018	0.9761	0.0095
ψ_5	D_1	2.0000	0.1000	1.7098	0.0513	0.9052	0.0080	0.8835	0.0076
ψ_6	D_2	1.0000	0.0100	0.1146	0.0013	−0.5329	0.0003	−0.0224	0.0009
ψ_7	N_1	0.0000	0.0010	−0.7668	0.0002	−0.8068	0.0002	−0.6854	0.0002
ψ_8	N_2	1.0000	0.0100	1.3835	0.0242	1.0194	0.0105	1.1410	0.0138