From inductive model-based control system design to deductive data-driven unfalsified adaptive control: A Philosophical

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***Abstract*—Feedback control loops are hidden but ubiquitous mechanisms all around the modern world. The current control technology utilizes model-based advanced control systems design. The philosophical background thought behind such designs is an inductivism-based reductionist-mechanistic approach. Despite its outstanding problem-solving achievements, it is argued that a deduction-based philosophical approach in the form of data-driven control system design has emerged. Unfalsified control is a notable outcome of philosophical thinking and is briefly reviewed.**

***Keywords*: Model-based control; Data-driven control; Falsification philosophy; Unfalsified control.**

I. INTRODUCTION

NATURE and biological systems have relied on self-regulating mechanisms for survival. A homeostasis that maintains stability and (optimally) regulates the conditions for endurance. Whenever this feedback mechanism fails, calamity or death ensues. Nature is continuously changing, yet the gift of feedback to nature is a dynamic equilibrium: evolutions with stability prevail. Disturbances and deteriorating external forces are always present and threaten life and stability. However, the built-in regulatory feedback mechanisms promptly and effectively respond to the deviations, and its convergent control establishes a new balance [1].

Man learning from nature developed and understood primitive feedback mechanisms long ago. Aristotle wrote in Politics, Book 1, Chapter 3 *"…if every instrument could accomplish its own work, obeying and anticipating the will of others … if the shuttle would weave and the pick touch the lyre without a hand to guide them, chief workmen would not need servants, nor masters slaves."* That clearly describes feedback.

Today, feedback is present everywhere around us. Feedback control owes its development as a field to contributions from engineers, scientists, mathematicians, economists, and *philosophers*.

Feedback control, as a branch of engineering science, has been developed in parallel with natural sciences. Discussions regarding strong similarities and fundamental differences between natural and engineering sciences are well developed, and their interactions in a knowledge-based ecosystem are studied and understood. Natural sciences found and explained the natural laws, while engineering sciences, based on the derived natural laws, recognized, invented, designed, and maintained artificially made engineered systems. However, the role of philosophy and philosophical insights in the development of engineering systems has not been deeply understood and realized by many engineers. In this paper, an introduction to the philosophical influences and their shadows on feedback control is sketched.

It has always been a challenge in the engineering and engineering scientists' communities to find the *system principles* that pave the path for effective understanding of complex physical systems, and provide sufficient insight and operative tools for designing complex man-made systems. Nevertheless, in most cases, engineers have ignored the philosophical background of such understandings and achievements. One such fundamental principle is the feedback mechanism and feedback control. Modern feedback control has three main elements:

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- System modelling
- System analysis
- Control system design

The primitive feedback control of ancient times was concerned with heuristic-artistic-innovation case-based designs. The applications were concerned with simple plant regulations, and this lack of modelling-analysis understanding was not a serious problem. This trend can be traced with limited exceptions up to the end of the nineteenth and early twentieth century. However, as in the early twentieth century, the number of feedback control and systems in industry multiplied, control system designers were confronted with two major problems that seriously slowed their scientific progress, and anomalies aroused in the control applications of emerging complicated applications [2]:

- Control system designers in different engineering fields utilized different symbolic representations for their problems that were not easily understood by other disciplines. This led to a lack of mutual-theoretical understanding with no common platform for discussion.
- The applied analysis and design methodologies were mainly case-based and not easily transferable to other engineers. In fact, the only available analysis tools were the differential equation theory and the algebraic stability criteria.

The grand revolution came with the mathematical modelling concept that allowed the application of advanced mathematical tools for control system analysis and design.

II.PHILOSOPHICAL DISCUSSIONS ON MODEL PREVALENCE IN FEEDBACK

Induction, *reductionism*, and *mechanism* are the main philosophical foundations and justifications for the substitution of a real physical phenomenon with various model forms in science and engineering [3], [4]. Where, in the control systems design and feedback context, models are predominantly mathematical models.

Following the Bacon's description of scientific methodology, in the model-based control system design techniques, physical facts and laws governing the dynamical systems are derived along with input-output observations and other available measurements to formulate a mathematical model of the dynamical systems. The model is then validated through simulations and experiments. This method of model derivation can be considered as *induction-based* [4]. Several prominent philosophers have raised considerable objections to the use of induction in scientific methodologies that will be discussed later.

However, there are philosophical questions regarding the ontology of model-based analysis and design approaches. From an ontological perspective of system dynamics modelling, three approaches are evident: Realism, Idealism, and Moderation. In the realism approach, a model is assumed to exist for all the natural phenomena. In the idealistic approach, models cannot describe natural phenomena and are only intellectually formed as mental concepts. In the moderate approach, systems can in some cases be described by models, and sometimes the phenomenon is so complex that it is beyond our comprehension [5].

Modeling and system dynamical behaviour analysis are key steps in current scientific and engineering methodologies. The general modelling cycle is depicted in Fig.1. *Explanation* and *confirmation* are fundamental to the system modelling cycle. Where, explanation is the basic understanding of the physical phenomenon with *assumptions*, *hypotheses*, *theories*, and *laws* as its core axis. In real-world applications, assumptions and hypotheses may vary with time, and this may enforce modifications in theories and laws. The explanation process involves *idealization* and *unification*. Idealization is the densification of empirical facts into a simple statement. In the densification procedure, some details are inevitably omitted. Idealization may also involve isolating the phenomenon from the environment and other elements, as in reductionism. Also, the unification of apparently unrelated phenomena is the other procedure in the explanation process. In the philosophy of science, confirmation indicates data and events that approve and support a scientific theory. In this procedure, different tests and experiments are performed to confirm a theory or a law to validate the assumptions and hypotheses. The confirmations can be qualitative or quantitative.

In Plato's view, gaining a true understanding of what is constantly changing is impossible [6]. The world of nature is constantly changing and true cognition cannot therefore be achieved. Plato argued that everything has a potentially perfect form. Accordingly, Plato does not consider sensory perception to be true knowledge. Plato's famous definition of knowledge is: "Knowledge is a justified true belief" [7]. Based on this, Plato advocates deductive reasoning. Deductive reasoning is a type of logical thinking that begins with a general idea and reaches a specific conclusion and is sometimes referred to as top-down thinking or moving from the general to the specific. A deductive approach is concerned with developing a hypothesis based on the existing theory, and then designing a research strategy to test the hypothesis.

On the other hand, Aristotle believed that inductive reasoning was necessary to establish some basic assumptions prior to scientific tests. Inductive reasoning makes generalizations from specific observations [8]. Inductive reasoning starts with data and then conclusions are drawn from the data. In causal inference inductive

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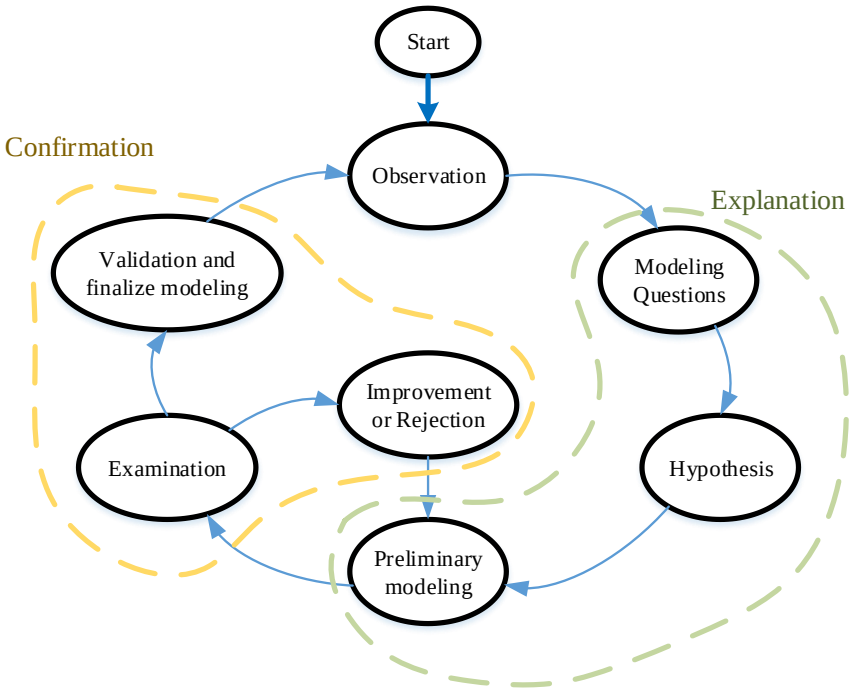


Fig. 1. The modelling cycle

reasoning, inductive logic is used to draw a causal link between a premise and a hypothesis. Aristotle used the term First principle (*Primum movens*) to prove his belief that states: knowledge gathering is the process of gaining experience from what we already know about the truth. He believed in the science of observations and measurements to create a general rule and construct a model.

Aristotle viewed scientific research as going from observations to general principles and returning to observations. He believed that the scientist should deduce the explanatory principles from observations and then deduce the theorems about phenomena deductively from the premises. In Fig. 2, both inductive and deductive reasoning are briefly demonstrated.

Inductive reasoning is the philosophical justification of system modeling. To summarize, based on system data, a model is developed (inductive logic) utilizing system identification techniques or modeling based on physical laws from the first principles. Then, the models are validated with the available information for confirmation (deductive logic), and finally, models are used for analysis, design, and simulations (inductive logic). A thorough background on the philosophical perspective of control system design is provided in the second chapter of the reference [9].

III.FOUNDATIONS OF THE MODEL-BASED CONTROL

A. GENERAL SYSTEMS THEORY

A system is defined as “a set of interrelated elements forming a collective entity, where related implies that information and/or energy are exchanged or shared between the elements” in [4]. In engineering, system elements can originate from different fields, such as electrical, mechanical, fluid, etc. It is important to note that by disjointedly considering and studying the elements of a system, and totaling the results, as in a reductionism regime, the system characteristics as a whole cannot be necessarily constructed. Moreover, the system characteristics can vary with time, while the elements disjointedly considered in a time interval may be time-invariant.

General systems theory focuses on system structure rather than its function. The theory suggests that complex systems, regardless of their purpose, have some basic principles of organization in common, and that these principles can be modeled mathematically. The theory was developed based on the work of Austrian biologist Ludwig von Bertalanffy, British economist Kenneth Boulding, and Russian-American mathematical psychologist Anatoly Rapoport [10]. Bertalanffy states the view and purpose of the general systems theory as follows [11]:

- Formulate the general system’s principles without

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regard to the specific form of its constituent elements and their relations.

- Formulate specific and precise rules for non-physical disciplines by analyzing the biological, social, and behavioral components of systems.

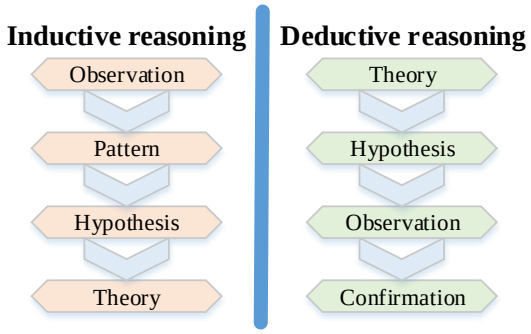


Fig. 2. Inductive reasoning vs. Deductive reasoning

- Establishment of an integrated basis and combination of scientific information through the emergence of isomorphism in various fields.

B. MATHEMATICAL MODELS

Mathematical modelling of dynamical systems radically changed the analysis and design of control systems, from a trial and error heuristic design based on personal inspirations to the systematic design process of classical and later modern control theory. Both classical and modern control design techniques are model-based. However, the classical control designs based on the input-output linear models were limited to linear time-invariant, single-input-single-output plants, in the presence of no interactions, noise, or severe disturbances. Modern control techniques based on internal state variable models overcame most of the problems associated with the classical control design approach.

The linear input-output model or the plant transfer function and the state-space internal model are developed using the physical laws governing the system, and (or) the system identification methods. Most of the pioneer researches in the field envisaged that the models were close to the true system. However, this proved to be not true in many applications.

The fundamental principle which supported the model-based design techniques is the certainty equivalence principle. A heuristic concept that permits the use of inaccurate current estimation of the plant's models, and permits controller designs based on the estimated model, although the error may not be small. Consequently, the philosophy of model-based control is stated as [12]: Estimate the best possible model, then design the controller based on this estimated model. According to the inductive logic, the fundamental structure of the model-based control system strategy is depicted in Fig. 3. The main purpose is to design an applicable and successful control system. Although the controller is designed for the model, it is ultimately applied to the actual system.

C. ROBUSTNESS, ADAPTATION AND INTELLIGENCE

Often in practice, it was observed that the performance of the implemented control system either failed or was not up to the expectations and closed-loop performance specifications. The postmodern control design techniques were promoted to handle the arisen crisis, also referred to as the theory-practice gap. These techniques were based on the robustness-adaptation-intelligence concepts.

The robust control approach was initiated in the 1980s to ensure closed-loop stability and performance in the presence of modelling errors and uncertainties [13]. In the case of large uncertainties and (or) time-varying parameters, adaptive control methodologies were introduced in the 1950s and have undergone substantial theoretical modifications and alterations in the past seven decades.

The original idea of adaptive control was taken from biology. Charles Darwin proposed the concept of natural selection to increase environmental compatibility through adaptation. In biological systems, the characteristics of the organism change with the help of natural selection and increasing compatibility with the environment [14]. The interpretation of adaptation was first introduced into the field of control engineering in [15].

A fundamental change in the adaptive approach prevailed in the late 1980s and early 1990s to handle the control of systems with rapid changes in structure or parameters [16]. The classical adaptive control approach was incompetent in dealing with such system variations [17]. Switching was introduced in the adaptive control scheme, and the adaptive switching supervisory control (ASSC) philosophy of control emerged.

The ASSC algorithms are depicted in Fig. 4. The task of the supervisor unit is to obtain an estimate of each controller's performance based on the system input-output data and select the appropriate controller using an appropriate cost function.

There are various methods proposed for the selection of controllers in the supervisory control. The supervisory control can be divided into three general categories: Pre-routed, Estimator-based, and Performance-based.

In the pre-routed and estimator-based methodologies, model plays a key role. The exact model matching condition highlights this dependency. To circumvent the need for models, the performance-based approach is proposed.

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The prominent performance-based supervisory control structures are the Unfalsified Adaptive Switching Control (UASC) [18] and the Multiple Models Unfalsified Adaptive Switching Control (MMUASC) structures [19]. The MMUASC approach combines features of the multiple models structure and the unfalsified control. Its important advantage over the multiple models methods is that it does not require the exact matching property.

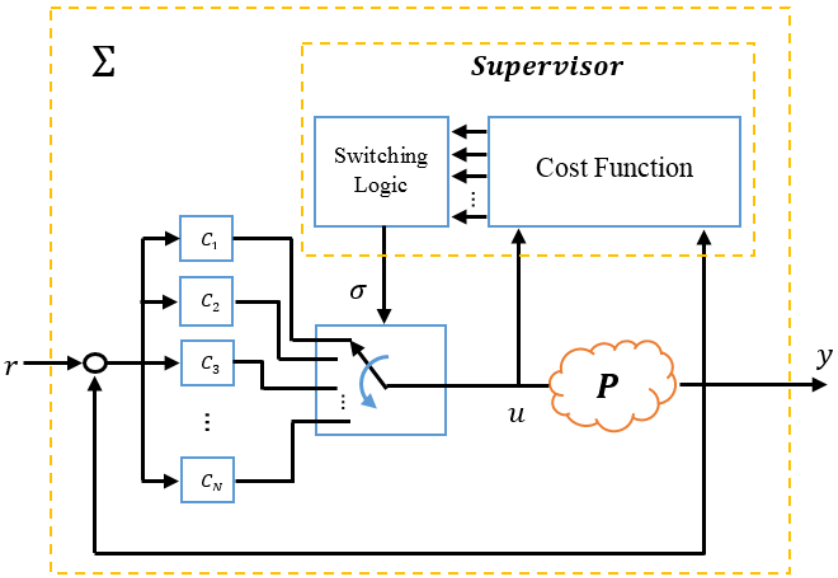


Fig. 4. The general structure of a switching supervisory control

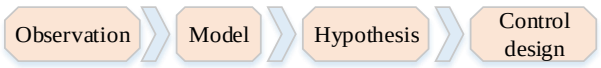


Fig. 3. Inductive logic in the model-based control design

IV. FALSIFICATION ALTERNATIVE TO INDUCTION-BASED FEEDBACK CONTROL PHILOSOPHY

A. THE PROBLEM OF INFINITE REGRESSORS

Once in the induction-based model-based control design regime, assumptions of different natures and sources appear. Assumptions such as linearity, non-linear structure, model orders or relative degrees, various defined bounds to be satisfied, uncertainty types, and various structural assumptions. Assumptions are the Achilles' heel of mathematical system theory [20]. If the modeling assumptions fail, the conclusions based on the failed assumptions are unreliable.

This series of assumptions and conclusions based on assumptions can be viewed as an infinite regressions, that is, an infinite series of units governed by a recursive principle. The recursion principle determines the dependency of respective units on their predecessor. Conclusions rest on assumptions and assumptions on assumptions and this is as depicted in Fig. 5, representing the well-known *turtles all the way down* situation [21].

An important example of the infinite regression problem is the Bayesian probability concept and the resulting estimation techniques [20]. Bayes' theorem for conditional probability gives:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (1)$$

Eq. (1) states that the posterior probability $P(A|B)$, that is the probability of the parameters A given the evidence B, is directly related to prior probability. Any attempt to estimate $P(A|B)$ requires an estimate of the prior probability in advance. This dependency leads to infinite regression and turtle's situations as, shown in Fig. 5.

The prior assumptions of mathematical modellings of real physical systems regarding their structures or properties are not directly deduced from the system, they are often derived from mathematical requirements for the application of a particular design theory, and are tested via an approximate mathematical model of the true system. Hence, such prior assumptions contravene the *hypothesis non fingo* of Isaac Newton [22].

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In a practical real-world system, the only available information that is directly deduced from the plant are the input-output observations. The derived physical laws and identified models are only approximations that often neglect interconnectedness and interactions with other elements and the environment. Such laws and derived models can be assumed to be valid for limited simple physical plants. Hence, to avoid the prior assumption dilemma in the control system analysis and design problems, data-driven control system design techniques with no assumption about the true system, noise, and disturbance, are the practical alternatives to the model-based approaches.

B. THE FALSIFICATION THEORY

Karl Popper's falsification theory in the philosophy of science provided the required platform for a data-driven control concept. Popper proposed the deductive-based methodology for scientific studies to replace the inductive-based methodologies. According to Popper, it is impossible to prove a scientific theory by induction, and that proper science comes from deduction with the process of *falsification*.

In the falsification process, all of the hypotheses should be tested. The Popper's methodology is also known as the *hypothetico-deductive* method. He replaced the classical observation induction-based methodology with falsification as the validity check for distinguishing a scientific theory from non-science, or what is called the *demarcation* theory. By advancing the method of experimental falsification, he rejected the idea that knowledge comes from analogy and classical reasoning (Aristotelian-Platonic), and he accepted the critical rationalism approach.

The falsification approach has been employed in the data-based control theory methodologies. Hypotheses are the basis of the model-based approach, and they are empirical estimates that describe a phenomenon. Then, through prediction or experimentation, the theories are validated. Prediction is an extrapolation from the current system's state, while experiments are verifications and investigations

designed to approve the system's relation. According to Popper, all of the predictions in the scientific theory should be tested, and the theory is rejected if it does not match with the test's results. From this viewpoint, the number of observations does not provide a proof justification and the possibility always exists that a future observation may falsify the theory. Hence, induction cannot prove a theory or provide certainty, and only one counterexample or observation is enough for falsification. The falsification theory has the following three features [23]:

- *Falsifiability*: Theories can be falsified if data from new observations (experiments) are in contrast to the theory.
- *Parsimony*: Theory should be simple and not require additional assumptions beyond those



Fig. 5. Assumptions on assumptions: turtles all the way down [21]

necessary for the observed data.
- *Validation*: Theory must be thoroughly validated with rigorous experiments that seek a counterexample.

C. Falsification in control engineering

The control design problems can be divided into four categories based on the following model availability cases:

- Accurate models
- Inaccurate models with well-defined uncertainties and satisfied assumptions
- Inaccurate models and uncertainties-assumptions fulfilments that cannot be guaranteed
- Model derivation is not feasible (physically, economically, etc.)

Model-based control theory can be successfully implemented in cases 1 and 2. Model-based control theory can be employed for case 3 in some plants with caution. Data-driven methodologies are strongly recommended for case 3 and inevitable for case 4.

The term falsifying was first used in engineering by Jan Camiel Willems for systems identification [24]. He proposed that a model is unfalsified if it contains all the available information from the system at that moment. Also, the *Most Powerful Unfalsified Model* (MPUM) is the model with the best data fit. Inspired by the Willems

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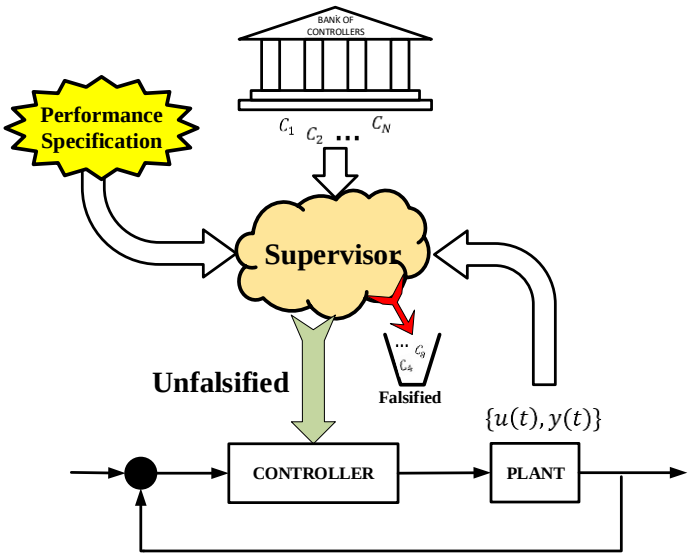


Fig. 6. Concept of the controllers' falsification

approach, Michael George Safonov introduced falsification into the field of control engineering. Unfalsified adaptive control algorithms are looking for a stabilizing controller with respect to the system input-output data with minimum assumptions [23].

Safonov first introduced the idea of falsifiability into the analysis and design of control systems in 1995 [25] and later in [18]. In the UASC method, instead of identifying a mathematical model for the system, a supervisor is trained according to the input-output data. Although no model for the system is used in the UASC itself, a model of the system is often used in the controller design. The avoidance of the model's direct use in this method provides a large workspace, which also includes indeterminate systems. The general structure of the UASC is the same as ASSC as depicted in Fig. 4. In this structure, the supervisor should select a controller from the existing pre-designed control set using the system data at different moments, and place it in the control loop.

As shown in Fig. 6, it is supposed that the input-output system data is available. The set of pre-designed controllers and the desired performance characteristics are already known. A controller is called unfalsified if it does not destabilize the system according to the existing system's data and also satisfies the performance criterion. Consequently, if a controller is falsified based on the input-output data of the system, it is not a stabilizer or does not provide the desired performance.

D. Principle of the Unfalsified Adaptive Control

According to Fig. 6, based on the system input-output data, controllers that do not fulfill the desired performance are rejected. This process is performed without placing the controllers in the control loop. An appropriate control set is assumed to be available. In the adaptive control literature, a control problem is *feasible* if there is at least one stabilizing controller in the control set. To evaluate the performance of inactive controllers, the supervisor uses the *virtual reference signal* concept that is derived from the system input-output data and the controllers' structure. The performance function, or the cost function, determines which controller has a superior performance solely based on the system input-output data. To picture the falsification philosophy in action for control system design, consider the following cost function

$$V(C_i, z, t) = \frac{\|W_1(y - \tilde{r}_i)\|_t + \|W_2\, u\|_t}{\|\tilde{r}_i\|_t + \epsilon} \qquad (2)$$

where $\| x \|_t = \sum_{i=0}^{t} \sqrt{x^2(i)}$ denotes truncated 2-norm, $z = [y, u]^T$ and $\tilde{r}_i$ are the closed-loop system input-output data and the virtual reference signal, respectively. W_1 and W_2 are proper weighting coefficients and ϵ is a small positive constant.

The *virtual reference signal* $\tilde{r}_i$ is defined with respect to the controller C_i. It is a hypothetical reference input that reproduces exactly the same input-output data up to time t, if the controller C_i was in the control loop. The virtual reference signal is used to evaluate controllers that are not actually active in the control loop. The virtual reference signal and a so-called *potential closed-loop* is shown in Fig. 7.

Note that C_i represents the controllers in the controller's bank, active or inactive. The input-output system data and the controller structure are used to calculate the virtual reference signal and no system model is required.

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If the controller C_i is minimum phase and proper, the virtual reference signal is obtained from the following equation

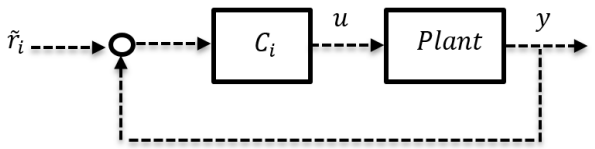


Fig. 7. The virtual reference signal in the potential loop

$$\tilde{r}_i(t) = C_i^{-1}u(t) + y(t) \qquad (3)$$

The minimum necessary condition for the closed-loop stabilization is feasibility. The adaptive control problem is *feasible* if there exists at least one stabilizing controller in the controller set at any time. To summarize, the falsification philosophy has provided a data-driven control design platform that is deductive-based and requires no prior system assumptions. By circumventing the need for mathematical induction-based models, it has widened the scope of practical control design implementations to complex plants where models are unavailable or non-feasible to derive.

V.CONCLUSIONS

The prevalence of models in the feedback control system designs is viewed from an induction-reductionism-mechanism based philosophical framework. Model-based analysis and design of feedback control systems naturally followed the mathematical modelling derivations. Nevertheless, a theory-practice gap manifested and the shortcomings of model-based techniques surfaced in real-world complex applications. To overcome the arisen challenge, the shift from induction to deduction in philosophical thoughts is necessary. This derived parts of the control scientists' community to the falsification theory of Popper and resulted in the data-driven unfalsified control design methodology.

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