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Research Paper

Modeling of Control Systems for Industrial Operations

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ABSTRACT: *This paper focuses on modeling of analogous physical systems and their applications in industrial operations and control. Methods adopted include use of differential equations, Laplace transform and transfer functions. A review of the developing trends in control of industrial operations and engineering applications towards novel control systems development was also made. Materials used were collected primarily from textbooks, journal articles from Research Gate, Google search engine, Google Scholar, IEE EXplore, CrossRef, and Science Direct databases. The study reveals that the importance of modeling control systems in industrial operations cannot be overstressed. Models discussed are analogs which are useful for the study, analysis and design of non-electrical systems like mechanical systems from analogous electrical systems. Hopefully, presentations made in the paper will assist engineering students and some other persons who are interested in the design and development of electromechanical systems in understanding how the various electrical and mechanical analogs relate and are formulated and utilized in research and development efforts.*
Key words: *Control, Modeling, Operation Processes, Analog Systems, Research and Development*

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Nomenclature

Symbol	Meaning	Symbol	Meaning
IT	Information technology	=	Equal to
SCADA	Supervisory control and data acquisition	F	Force
DCS	Distributed control systems	M	Mass
PLC	Programmable logic controllers	ϕ	Magnetic flux of current
HMI	Human-machine interfaces	q	Amount of charge on conductor
CNC	Computer numerical control	$\int$	Integral of
LTI	Linear time invariant	$\sum$	Sum of
LF	Transfer function	x	Linear displacement in x direction
LT	Laplace Transform	y	Linear displacement in y direction
i	Current	t	Time
i_n	n^{th} current	$x(t)$	Input of an LTI system
V	Voltage	$y(t)$	Output of an LTI system
V_n	n^{th} voltage	$X(s)$	Laplace Transform of an LTI input
e	Energy	$Y(s)$	Laplace Transform of an LTI Output
v	Velocity	ω	angular velocity
θ	angular displacement of a shaft	J	Moment of inertia
T	Torque	Fig.	Figure
N	Number of branches, nodes, elements, etc depending on the system under reference	Eqn.	Equation

I. INTRODUCTION

Every profit oriented establishment aims at reducing waste, including downtime, and increasing production targets. Achievement of this aim depends to a large extent on the management's policies and how the systems on ground are coordinated and maintained. Control of industrial operations is a strategy employed in an industry for effective and efficient manufacturing, assembling, warehousing, raw materials processing and distribution lines. A manufacturing outfit wishing to be sustainable and viable in business must have its production line, control/coordination of materials, equipment, and human resources defined and operated in a manner that allows for production and operating efficiencies. In a work flow shop, two key aspects of the production control are routing and scheduling. Routing is a deliberate action of setting out of a work flow and the machines involved in the sequence they should go in a production line so as to reduce downtime and increase production targets. A good routing aims at reducing wastes, including unnecessary costs incurred in a production system. On the other, scheduling is the allotment and controlling of the time required for each step taken in production process to be completed.

Meanwhile, the part of a system primarily concerned with maintenance of the performance specifications is referred to as the controller (or control). Most industrial machines are mechanical by design but are electrically operated. Such machines include robots, powered by electric motors or other actuators manipulated by means of electrical circuitry. The latter is used to turn them off or on at the appropriate time, control their speed of operation, and to achieve other specifications. There are a lot of controls going on in our homes and cars as well.

1.1 Components of Control Systems in Industrial Operations

The basic components of a control system are made up of an input (objective/target), the control element and the output (feedback/result). Two main branches of control systems known to exist are Open-loop (non-feedback system) and Closed-loop (feedback system), represented in Figs. 1 and 2 respectively.

Figure 1: A simple open-loop system

As can be clearly seen, the open-loop system does not have means of monitoring or comparing outcome with an expected result; whereas the closed-loop system depicted in Fig. 2 incorporates an automatic mechanism for ensuring that the actual outcome is close to the expected result.

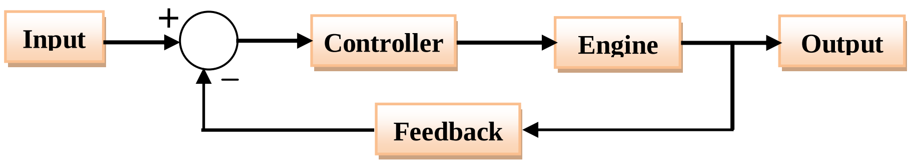

Figure 2: A simple closed-loop system

1.2 The Role of Control Systems in Industrial Operations

The term "industrial control system (ICS)" is used in a general form encompassing several types of control systems such as SCADA systems, DCS and PLC often found in the industrial sectors and critical infrastructures. An ICS may contain numerous control loops, HMI, remote diagnostics, and maintenance tools built using an array of network protocols. A system can be configured to operate in an open-loop mode controlled by means of established settings, and in manual mode controlled completely by humans [1]. In closed-loop control systems, the output has an effect on the input in such a way as to maintain the desired objective. The present day ICS evolved from insertion of IT capabilities into existing physical systems to replace or supplement physical control mechanisms. Introduction of IT capabilities into physical systems goes with emergent behavior that has some safety, security, privacy, and environmental implications. Consequently, this calls for research on development of engineering models and analysis to address these concerns.

From the foregoing, therefore, for a production process to be successfully carried out, there must be an operation and control system to guide the operation. This is achieved by means of control loops, designed to keep the process variable at the desired set point(s). Fig. 3 represents a typical ICS which contains numerous control loops with human interfaces. The remote diagnostics and maintenance tools of the system are built using an array of network protocols on layered network architectures. A sensor is a device that produces a measurement of some physical property and then sends this information as controlled variables to the controller. The controller interprets the signals and generates corresponding manipulated variables, based on a control algorithm and target set points, which it transmits to the actuators. Actuators such as control valves, breakers, switches, and motors are used to directly manipulate the controlled process based on commands from the controller [3].

Moreso, worthy of mention is simulation of a process or system in industrial control design which allows for complex what-if scenarios involved in the system to be viewed and better analyzed. Two known components of an industrial control systems are namely, process control – for process modeling, and system control which allows for system modeling. Process modeling is the mathematical representation of a process by application of material properties and physical laws governing geometry, dynamics, heat and fluid flow, and so on, in order to predict its behavior [2]. The paper also presents system modeling as a system typically composed of a number of networks that connect its different nodes and the networks, interconnected through gateways. This postulates that models and simulation features should form part of a larger toolset that supports the design of control systems for both domestic use and for industrial operations.

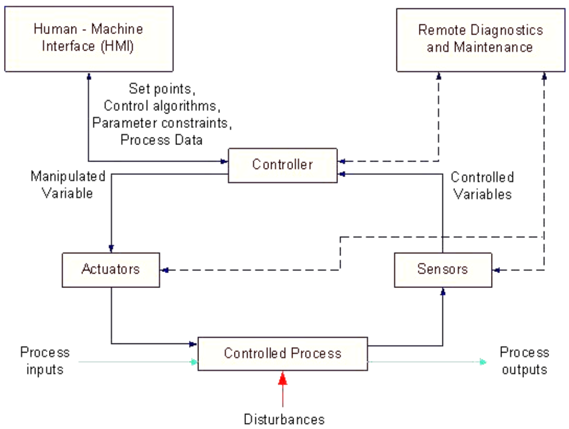

Figure 3: A typical of an industrial control system [3]

Operators and engineers use human interfaces to monitor and configure set-points, control algorithms, and to adjust and set up parameters in the controller. The human interface also displays process status information and historical information. Diagnostics and maintenance utilities are installed to protect a system or help the system recover from abnormal operations or failures.

II. DEVELOPING TRENDS IN INDUSTRIAL CONTROL – a Brief Review

Types of industrial control systems include adaptive control, observer-based control, model-predictive control, time-delay control and long-time process control systems. Various researchers have worked hard to develop these areas to their present stages.

An extensive review of adaptive machining control (AMC), touting its evolution as a response to subjective judgment by part programmers was made by Koren [4]. The paper discussed basic classes of adaptive control: adaptive control with optimization (ACO), adaptive control with constraints (ACC), and geometric adaptive control (GAC), as well as self-tuning control approaches; reporting that a key drawback at the early stage of the system's development was lack of reliable sensing for germane phenomena such as tool wear or friction, or prohibitive cost for force and torque sensing. Landers, Ulsoy, and Ma [5] surveyed model-based machining control approaches using force information. The paper contrasted four control approaches - linearization, log transform, nonlinear, and robust - in terms of stability and robustness.. It concluded that such model-based approaches are insensitive to un-modeled dynamics, and that the choice of control is dictated by economics. Landers and Ulsoy [5], carried out early implementation of model-based machining control for force as Elbestawi had for accuracy in turning [6].

Observer-based adaptive control strategy has been applied in disturbance force rejection machining with sustainability objective [7]; while constraint-based adaption was used for geometric optimization of corner cutting in molds. This has driven new research in more accurate chip thickness models.

External disturbances in addition to modeling error and parameter variations contribute the most to the inaccuracy observed in motion system such as servomotors of the machine tools. Huang *et al*. [9] used the Disturbance Observer (DOB) approach proposed by Ohnishi [10] to estimate and compensate for the uncertainties in velocity and current loop of a CNC servomotor, and further included an adaptive tuning of motor inertia and viscous damping coefficient. By using this method over conventional PI controller, the accuracy of circular trajectory and reduced roundness error could improve by 84% [11]. DOB was used in the speed control loop for compensating speed fluctuations in constant velocity motion and a static friction model was obtained (ignoring the dynamic effects of friction on motion accuracy) based on position-dependent perturbation [12]. DOB as an effective control scheme has also been used for dual-drive systems in gantry NC machines to improve the synchronization error of double drive motors [13]. Adaptive Disturbance Compensation (ADC) control with LuGre dynamic friction model against PI controller was tested for speed control of servo-systems in circular motion [14]. Having the essential features of adaptive controllers, the ADC method is capable of mitigating uncertainties and disturbance by adjusting the observer gains. Sliding Mode

Control (SMC) is another control approach utilized for compensating disturbances and parameter variations in various systems [15], [16], and [17]. Adaptive SMC was successfully applied in Sencer and Shamoto [18] for mitigating the harmonic torque ripples in servo-drives. In the works done by Xi *et al*. [19] and Li *et al*. [20], dual SMC was successfully used for contouring error estimation of 5-axis CNC machine.

As a class of model-based approach, model-predictive process control emerged in the second half of the 20th century in continuous process industries such as pharmaceuticals and petroleum in order to minimize quality variability as cost was reduced. The approach is widely used today in the chemical industry, and has begun finding application in other manufacturing sectors [21]. The basic approach is shown in Fig. 4.

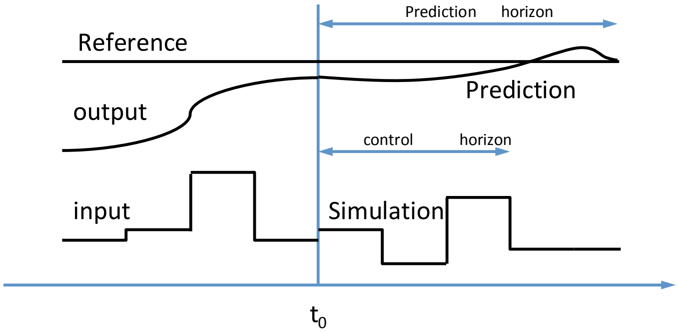

Figure 4: Model Predictive Control [21]

Model Predictive Control (MPC) for contour error mitigation enables the users to estimate the error in finite time interval, i.e. the prediction horizon, and tune the control input accordingly. Yang *et al*. [22] used a MPC scheme for contour error compensation in a 2-axis drive system and compared it to the conventional error-mitigation strategy of Zhang *et al*. [23]. Significant improvement was achieved specifically in the sharp corners [22],[23]. A linear time varying MPC was utilized in Lam *et al*. [24] to show a trade-off between accuracy and time. However the controller was only capable of operating up to 4ms (far from real-time industrial controller speed). In Stephens *et al*. [25], the authors discussed the computational cost of using MPC in high rate servo-systems and introduced a trajectory horizon (in addition to the prediction horizon) into the MPC scheme to lower the computational burden and reached satisfactory performance (with 100 µs sampling period) compared to traditional MPC. A MPC scheme with adaptive feed rate control for tracking diamond and freeform contours in high feed rate motions were also adapted in Tang and Landers [26]. Conway *et al*. [27] introduced a polynomial root finding algorithm for extracting tool path/contour error measurement in Cross-Coupled Controllers (CCC). This serves as an approximate contour error measurements replacement strategy for the control input of one axis influenced by the error in other axis. Stemmler *et al*. [28] applied MPC in decoupling machining process from the system control and predicted the unknown states through Kalman estimation, accounting for computational time delays.

Difficulty in applying the online estimation technique to strike a balance between a more accurate computational expensive model and the departure from an ideal control state, due to introduction of time delay and use of linearized model, led to the development of the Smith predictor model. This model was targeted at hybridizing predictive and feedback controls in order to deal with time-delay in the system. The basic architecture is given as in Fig. 5. The model provides an inner loop to address time delay introduced by model calculations by way of using a generalized system model in predicting the behavior the actual feedback signals to the controller. The Smith predictor has been variously implemented, including in vision-based positioning processes, where the servo is driven to bring a part targeted into a camera frame of reference, necessitating computationally-expensive image processing [29].

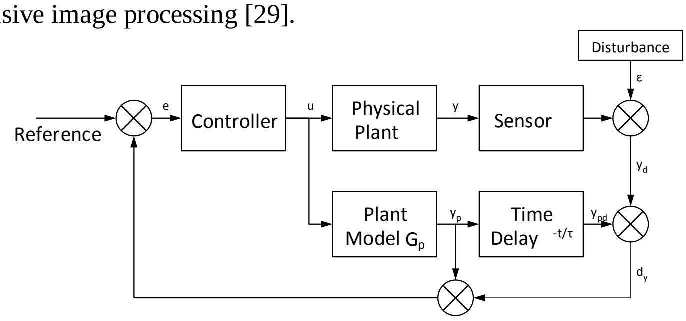

Figure 5: Smith predictor model [21]

Variables or states on which to control by model vary by process, but nominally include states which are not directly observable but which may carry a large influence on the process output. For machining, process variables such as true position, force, friction, and wear are employed, as well as output quality states such as dimensional consistency, surface condition, and residual stress profile, each somewhat difficult to assess in real time at the machining center. Such control approaches have been implemented recently directly to manufacturing processes, particularly machining. Researchers at Nanjing have proposed new approaches to 5axis machine tool error compensation [30]. Shin *et al*. [31] at NIST are using virtual machining models to generate data needed for open-architecture platforms and protocols such as the emerging MTConnect.

Meanwhile, despite several control approaches being proposed over the years in disturbance/uncertainty mitigation and improving contour accuracy, one major drawback is the fact that current industrial CNC machines do not allow for overriding their control algorithms in order to keep the stability in all cutting conditions [22]. The MTConnect open protocol serves as a universal language of obtaining information from the machine and is only a read-only protocol in the market. Therefore, pre-compensation of contour error and making modification beforehand in servo-axis motion is an alternative solution to work-around the accessibility to the machine control unit. A pre-compensating contour error strategy was introduced, taking into account the residual vibration of machine structure and axis limited bandwidth, in high speed motion of a 2-axis machine which was later implemented on a 5-axis CNC machine for high acceleration/jerk cutting [23]. A great deal of research work led by Yusuf Altintas at the University of British Columbia focused on implementing pre-compensation contour error for improving dimensional tolerances in machine tools [23], [33], and [34].

Machine health monitoring and prognosis can be viewed as a long-time feedback loop where model information is generated and evaluated. To that end, Wang *et al*. [35] uses probabilistic model-based approach for machinery condition evaluation. Zhu, DeVor and Kapoor [36] were some of the first to use a model-based approach to fault diagnosis in ball-end milling, a difficult model to implement due to complexity [36]. Part and fixture flexibility and friction are simultaneously evaluated and fed to a control scheme in Zhang *et al*, [2]. These approaches have been applied in other areas of manufacturing as well. As machining processes evolve, new implementations require new control measures. Model-based stability prediction and control of a machining robot was investigated by Mousavi *et al*, [37]. Cen *et al*. [38] worked on wireless force sensing and its use in control for robotic machining. Lu *et al*, [39] incorporated model based observers for tension control in steel strip manufacturing, while Itoh *et al*, [40] applied model-based control of rotational speed in a form rolling machine to eliminate transient vibration. Rabani *et al*, [41] executed an Iterative Learning Control (ILC) for estimating and prescribing the depth of a waterjet cutting process. Further still, surface roughness control in this type of process was predicted by Mohamad *et al*, [42]. Davis *et al*. [43] described observer-based adaptive control of friction stir welding; even human behavior is included in such approaches. An interval control approach for machine-assisted feedback to a manual welding operation was discussed by Huang *et al*, [9].

An aligned benefit to the predictive control approach in manufacturing is the ability to estimate the process and output states in real time. This information can be incorporated to machine or process health assessment programs, and is also of key importance to creating the process "digital shadow" or "digital twin" for incorporation to digital manufacturing approaches on the shop floor. Researchers at Nagoya are applying this identification approach to identify and share cutting process parameters for flexible parts [44]. This builds on similar work by Karpat *et al* [45], who used machining output to estimate constitutive material parameters. Using this per-piece knowledge estimate, system-level control can be improved by passing not only the physical part from process to process, but concurrently estimates about its material, condition, and behavior in the process in order to adapt and optimize in real time. Therefore, state estimation is an essential benefit of predictive and observer-based control approaches.

III. MODELING OF PHYSICAL CONTROL SYSTEMS

The method adopted in this paper is using electrical and mechanical analogs to model physical systems. Physical systems are idealized systems in which physical objects are connected in a way that allows them to perform defined objectives. It is hard to represent any physical system in its real form, hence the need to make assumptions when analyzing and/or synthesizing systems.

It is a common practice when determining the performance and transfer function of a control system to draw the block diagram and write mathematical equations of the basic laws governing the system as models representing the system. Such mathematical models include differential equation model and transfer function model.

3.1 Considerations Made

Some of the considerations/assumptions usually made when modeling for physical systems [46] include:

I. For Force-Current analogy

✓ Masses in parallel combination in a mechanical system have similar force.

- ✓ Elements in parallel combination in an electrical network have the same voltage across them.
- ✓ Each separate mass of a mechanical system corresponds to a separate node in the analogous electrical network.
- ✓ The number of masses present in a given mechanical system is equivalent to the number of nodes in its similar electrical network.
- ✓ For a given number of components in between two separate masses in a mechanical system, the same number is also connected in between two separate nodes in the electrical network.

II. For Force-Voltage analogy

- ✓ Each mass in a mechanical system corresponds to a separate node, and represents a separate closed loop in the equivalent electrical network.
- ✓ The number of masses in the mechanical system is equivalent to the number of meshes in the electrical system.
- ✓ An element existing between two masses in the mechanical system represents common elements between two meshes of the electrical system.

3.2 Differential Equation Model

Analogous electrical and mechanical systems will have differential equations of the same form [47]. Two main methods of obtaining electrical and mechanical analogous systems and some of the basic laws governing the systems, with their analogous relationships are summarized in Table 1.

Table 1: Analogous quantities and their relationships

Electrical		**Mechanical Analog I** *Force-Current*		**Mechanical Analog II** *Force-Voltage*	
Quantity	Equation	Quantity	Equation	Quantity	Equation
Voltage, V	$= i.\mathrm{R}$	Velocity, v	$= \frac{\mathrm{f}}{\mathrm{B}}$	Force, F	$= \mathrm{v.B}$
	$= \mathrm{L}\frac{di}{dt}$		$= \frac{1}{\mathrm{K}}\frac{df}{dt}$		$= \mathrm{M}\frac{d\mathrm{v}}{dt} = \mathrm{M.a}$
	$= \frac{1}{\mathrm{C}}\int i.dt$		$= \frac{1}{\mathrm{M}}\int \mathrm{f}.dt$		$= \mathrm{K}\int \mathrm{v}.dt$ $= \mathrm{K}.x$
	$\sum_{Loop} \mathrm{v}_n = 0$ (Not used explicitly)		$\sum_{Loop} \mathrm{v}_n = 0$ (Not used explicitly)		$\sum_{Object} \mathrm{F}_n = 0$
Current, i	$= \frac{1}{\mathrm{L}}\int \mathrm{e}.dt$	Force, F	$= \mathrm{K}\int \mathrm{v}.dt$ $= \mathrm{K}.x$	Velocity, v	$= \frac{1}{\mathrm{M}}\int \mathrm{f}.dt$
	$= \mathrm{C}.\frac{de}{dt}$		$= \mathrm{M}\frac{d\mathrm{v}}{dt} = \mathrm{M.a}$		$= \frac{1}{\mathrm{K}}\frac{df}{dt}$
	$\sum_{node} i_n = 0$		$\sum_{Object} \mathrm{F}_n = 0$		$\sum_{Loop} \mathrm{v}_n = 0$ (Not used explicitly)
Resistance, R	$= \frac{\mathrm{e}}{i}$	Lubricity (inverse friction)	$= \frac{1}{\mathrm{B}}$	Frictional Coefficient, B	$= \frac{\mathrm{f}}{\mathrm{v}}$
Capacitance ,C	$= \frac{q}{\mathrm{V}}$	Mass, M	$= \frac{\mathrm{F}}{\mathrm{a}}$	Compliance (inverse spring constant)	$= \frac{1}{\mathrm{K}}$
Capacitor energy, e_c	$= \frac{1}{2}\mathrm{C.e}^2$	Mass energy, e_m	$= \frac{1}{2}\mathrm{C.v}^2$	Spring energy, e_s	$= \frac{1}{2}\mathrm{K}.x^2$ $= \frac{1}{2}\mathrm{K}.(\frac{\mathrm{f}}{\mathrm{K}})^2 = \frac{\mathrm{f}^2}{2\mathrm{K}}$
Inductance, L	$= \frac{\phi(i)}{i}$	Compliance, (inverse spring constant)	$= \frac{1}{\mathrm{K}}$	Mass, M	$= \frac{\mathrm{f}}{\mathrm{a}}$
Inductor energy, e_L	$= \frac{1}{2}\mathrm{L}.i^2$	Spring energy, e_s	$= \frac{1}{2}\mathrm{K.x}^2$ $= \frac{1}{2}\mathrm{K}.(\frac{\mathrm{f}}{\mathrm{K}})^2 = \frac{\mathrm{f}^2}{2\mathrm{K}}$	Mass energy, e_m	$= \frac{1}{2}\mathrm{C.v}^2$
Power, P	$= \mathrm{e}.i$	Power, P	$= \mathrm{f.v}$	Power, P	$= \mathrm{f.v}$
Transformer	$\mathrm{N}_1:\mathrm{N}_2$ $\frac{\mathrm{e}_1}{e_2} = \frac{\mathrm{N}_1}{N_2} = \frac{i_2}{\mathrm{i}_1}$	Lever	$\mathrm{L}_1:\mathrm{L}_2$ $\frac{\mathrm{v}_1}{v_2} = \frac{\mathrm{L}_1}{L_2} = \frac{\mathrm{f}_2}{\mathrm{f}_1}$	Lever	$\mathrm{L}_1:\mathrm{L}_2$ $\frac{\mathrm{f}_1}{f_2} = \frac{\mathrm{L}_1}{L_2} = \frac{\mathrm{v}_2}{\mathrm{v}_1}$

3.2 Transfer Function Model

This is an s-domain mathematical model of control systems. An LTI system having x(t) and y(t) as its input and output respectively and its corresponding Laplace transforms as X(s) and Y(s) will have the TF obtained from the relation,

$$\mathrm{TF} = \frac{\mathrm{Y(s)}}{\mathrm{X(s)}} \qquad (1)$$

Eqn. (1) is depicted in Fig. 6, with a block having transfer function of an input X(s) and an output Y(s) inside of it.

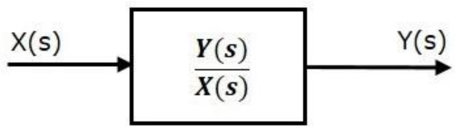

Figure 6: Transfer function model of a linear time invariant system

IV. AREAS OF APPLICATION OF ANALOGOUS CONTROL SYSTEMS MODELS IN INDUSTRIAL OPERATIONS

4.1 Modeling of Mechanical Systems

Two existing types of mechanical systems are linear translational mechanical systems and rotational mechanical systems. Various quantities used in mechanical systems are contained in Table 1. In linear mechanical systems, the basic variables include F, v, x, M, B and K, considering Fig. 7. For a Force-Voltage analogy, consider Figs. 7 and 8. In rotational mechanical type of systems, variables used include T, ω, θ; J and B (coefficient of rotational friction). Fig. 10 refers.

Fig. 7 is an ideal linear system with negligible friction and elasticity. F is applied.

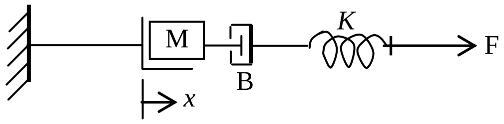

Figure 7: A linear translational mechanical system

Fig. 7, it can seen that by Newton's second law, the opposing force in each of the three mechanical elements

$$F_1 = M\frac{d^2x}{dt^2} \qquad (2)$$

$$F_2 = B\frac{dx}{dt} \qquad (3)$$

$$F_3 = kx \qquad (4)$$

Joining Eqns. 2 to 4 in accordance with Newton's second law of motion, the force balance equation for this system is

$$F = F_1 + F_2 + F_3 \qquad (5)$$

$$F = M\frac{d^2x}{dt^2} + B\frac{dx}{dt} + kx \qquad (6)$$

Or

Substituting Eqn. 6 for Eqn. 5 and taking the Laplace transform, the transfer function is obtained as,

$$F = \frac{1}{M s^2 + Bs + K} \qquad (7)$$

Eqn. 7 is the mathematical model of the given mechanical control system**.**

Consider also the electrical circuit whose input voltage is V, shown in Fig. 8. The system consists of a resistor, an inductor and a capacitor which are connected in series.

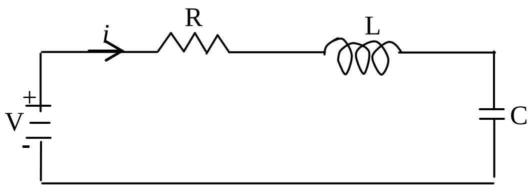

Figure 8: An electrical system

The mesh circuit equation for the system is written thus

$$V = L\frac{d^2q}{dt^2} + R\frac{dq}{dt} + \frac{q}{C} \tag{8}$$

Compare the coefficients in Eqns. 6 and 8 and see the analogy in the two systems.
Applying Laplace transform on both sides of Eqn. 8 and simplifying the expression

$$\left(\frac{1}{LC}\right) V_i(s) = s^2 V_o(s) + \left(\frac{sR}{L}\right) + V_o(s) + \left(\frac{1}{LC}\right) V_o(s) \tag{9}$$

$$= \{s^2 + \left(\frac{R}{L}\right)s + \frac{1}{LC}\}V_o(s) \tag{10}$$

$$\frac{V_o(s)}{V_i(s)} = \frac{\frac{1}{LC}}{s^2 + \left(\frac{R}{L}\right)s + \frac{1}{LC}} \tag{11}$$

Eqn. 11 is a transfer function of the second order electrical system whose transfer function model is as shown in Fig. 9 as a block having the transfer function inside it with an input $v_i(s)$ and an output $v_o(s)$.

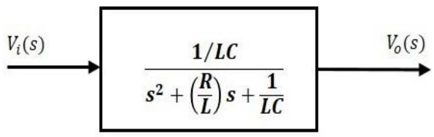

Figure 9: Transfer function model of second a order electrical system

By the same line of foregoing discussions, for Torque-Voltage analogy, consider a rotational mechanical type of system which has θ as the angular displacement (see Fig. 10). The torque (which is analogous to force) balance equation can be written as,

$$T = T_1 + T_2 + T_3 \tag{12}$$

Or

$$T = J\frac{d^2\theta}{dt^2} + B\frac{d\theta}{dt} + k\theta \tag{13}$$

Assuming all the initial conditions are considered zero, the LT of each part of Eqn. 13 can be taken and the TF generated.

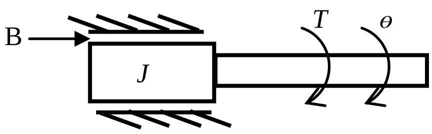

Figure 10: Rotational mechanical system

4.2 Modeling of Electrical Systems

Consider an electrical system which has all its elements: current source, a resistance, a capacitance and an inductor, connected in parallel as shown in Fig. 11. By means of this circuit diagram, it is possible to discuss Current-Force analogy of electromechanical systems.

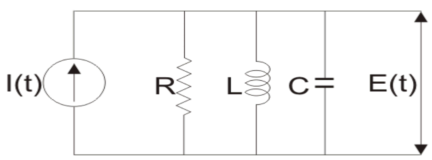

Figure 11: Representation of an electrical system [48]

From the circuit diagram, we know that

$$V = E(t) = \frac{d\psi}{dt} \tag{14}$$

And the circuit's nodal equation is

$$i = \frac{V}{R} + \frac{1}{L}V\int dt + C\frac{dV}{dt} \tag{15}$$

With the help of KVL equation, the expression for voltage can be written in terms of charge, resistance, capacitor and inductor. Hence, substituting Eqn. 14 into Eqn. 15 and simplifying

$$i = C\frac{d^2\psi}{dt^2} + \frac{1}{R}\frac{d\psi}{dt} + \frac{1}{L}\psi \tag{16}$$

V. CONCLUSION

Modeling of analogous systems of electromechanical devices and machines in industrial operations and control was studied and analyzed in this paper. The study revealed that the importance of modeling control systems in industrial operations cannot be overstressed. The models are useful for the study, analysis and design of non-electrical systems like mechanical systems from analogous electrical systems. Analysis of a control system means finding the output when the input and the mathematical model are known; while design of a control system implies finding the mathematical model when the input and the output are known.

The paper also show that and how the mathematical equations of translational mechanical system can be compared with the mesh equations of electrical system in Force-Voltage analogy, but compared with the electrical system nodal equations in Force-Current analogy. However, in rotational mechanical system, its mathematical equations are compared with mesh equations of the electrical system in Torque-Voltage analogy, but compared with the nodal mesh equations of the electrical system in Torque-Current analogy.

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